# Land Type Classification using Sentinel-2 Satellite Images

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# Abstract

This project presents a deep learning workflow for land-type classification using the EuroSAT dataset derived from Sentinel-2 multispectral imagery. Unlike conventional approaches that rely solely on RGB composites, this study leverages the full spectral richness of **13 Sentinel-2 bands**, capturing information across the visible, red-edge, near-infrared, and short-wave infrared regions. The use of multispectral data enables more accurate discrimination between land-cover types and enhances the model's ability to extract meaningful environmental features.

The proposed pipeline includes data preprocessing, exploratory analysis of multispectral distributions, feature normalization, and the development of two convolutional neural network architectures: a custom CNN and a **modified VGG16** adapted to accept 13-channel inputs. Extensive experiments demonstrate that the modified VGG16 architecture provides superior performance, achieving high accuracy and robust classification results across multiple land-cover categories.

This work highlights the value of multispectral information in remote sensing and demonstrates a scalable, deployable deep learning framework for automated land-type mapping and environmental monitoring.

# Acknowledgments

We express our sincere gratitude to everyone who contributed to the completion of this project. We extend our appreciation to the mentors, instructors, and colleagues whose guidance and feedback played an essential role throughout the development process. Their support greatly enhanced our understanding of multispectral data processing, deep learning methodologies, and remote sensing applications.

We also acknowledge the creators and maintainers of the **EuroSAT** dataset and the **Sentinel-2** mission, whose openly accessible multispectral imagery enabled the experimental foundation of this work. Additionally, we recognize the developers of the open-source tools and libraries—such as TensorFlow, Keras, NumPy, Matplotlib, and Scikit-learn—that powered the implementation and analysis phases of this project.

Finally, we extend our appreciation to team members for their commitment, collaboration, and continuous effort in building a complete and functional land-type classification system.

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# Chapter 1 – **Introduction**

Satellite imagery has become a critical resource for understanding land-use and land-cover patterns across diverse geographic regions. Recent advances in remote sensing technologies particularly multispectral imaging have enabled more detailed environmental analysis by capturing information beyond the visible spectrum. Among the most widely used Earth observation instruments is the **Sentinel-2** mission, which provides rich multispectral data across **13 spectral bands**, covering visible, red-edge, near-infrared, and short-wave infrared regions. These bands offer unique insights into vegetation health, soil structure, water content, and built-up areas, making Sentinel-2 a powerful foundation for land-type classification tasks.

The **EuroSAT dataset**, derived from Sentinel-2 imagery, serves as a standardized benchmark for land-cover classification research. It contains well-curated image patches categorized into ten distinct classes, representing both natural and human-made environments. Leveraging such a dataset allows machine learning models to learn spatial and spectral signatures associated with different land types.

Deep learning has emerged as the leading approach for satellite image interpretation, particularly through the use of **Convolutional Neural Networks (CNNs)**. However, many conventional architectures—including the original VGG16—are designed specifically for three-channel RGB images. Applying these models directly to multispectral data requires architectural modifications to accommodate the additional spectral information. This project addresses this challenge by adapting the VGG16 architecture to accept **13 spectral channels**, enabling the model to exploit the full richness of Sentinel-2 data.

The objective of this project is to develop a complete deep learning pipeline for **automated land-type classification** using the EuroSAT 13-band dataset. The workflow includes data exploration, preprocessing, feature normalization, model design, training, evaluation, and deployment. A comparative study between a custom-built CNN and a modified 13-band VGG16 model is conducted to identify the most effective architecture for multispectral classification.

This chapter introduces the overall context of multispectral remote sensing and establishes the significance of leveraging all 13 Sentinel-2 bands for improved land-cover classification accuracy. The subsequent chapters detail the methodologies, experimental design, results, and conclusions drawn from this work.

# Chapter 2 – **Background & Motivation**

Understanding land-use and land-cover patterns is essential across numerous domains, including environmental monitoring, agricultural management, climate analysis, and urban planning. Remote sensing technologies have significantly advanced these capabilities by providing continuous, large-scale views of the Earth's surface. Among the most impactful innovations in this field is **multispectral imaging**, which captures reflectance information across numerous wavelength regions. Unlike traditional RGB imagery—limited to only three color channels—multispectral data provides richer and more discriminative features for differentiating diverse land types.

The **Sentinel-2 mission**, operated under the Copernicus program, delivers high-resolution multispectral imagery through **13 spectral bands** spanning the visible spectrum, multiple red-edge channels, near-infrared (NIR), and short-wave infrared (SWIR). Each band highlights different environmental characteristics such as vegetation health, soil moisture, water content, and urban surface properties. This spectral diversity forms a powerful foundation for automated land classification, enabling machine learning models to detect subtle patterns that are not visible in RGB images.

Deep learning, and particularly **Convolutional Neural Networks (CNNs)**, has transformed image classification by enabling models to automatically learn spatial and spectral patterns. However, most conventional CNN architectures—such as the original VGG16—are designed for three-channel RGB inputs. Extending these models to multispectral data requires architectural adjustments, including modifying the input layer and adapting convolutional filters to handle higher-dimensional spectral information. This project addresses these challenges by developing a **custom CNN** and modifying **VGG16** to accept **13-channel inputs**, enabling the extraction of deeper multispectral features.

The motivation behind this project stems from the need to evaluate how effectively deep learning models can leverage the full multispectral richness of Sentinel-2 data. By comparing a simpler CNN to an enhanced 13-band VGG16 model, the study aims to highlight the advantages of deeper architectures in capturing subtle land-cover distinctions. The broader goal is to design a robust, scalable, and deployable framework capable of supporting real-world environmental monitoring, smart agriculture, and geographic information systems (GIS) applications.

# Chapter 3 – **Literature Review**

Research in remote sensing and land-cover classification has significantly evolved with the increasing availability of multispectral and hyperspectral satellite imagery. Traditional approaches relied heavily on handcrafted features, spectral indices, and statistical models to interpret Earth observation data. However, with the emergence of deep learning—particularly convolutional neural networks (CNNs)—the field has shifted toward data-driven feature extraction capable of learning complex spatial and spectral relationships directly from raw imagery.

**Multispectral Remote Sensing:**
Sentinel-2 imagery, with its **13 spectral bands**, has been widely recognized for its ability to capture a broad range of environmental characteristics. Studies show that combining information from visible, red-edge, near-infrared (NIR), and short-wave infrared (SWIR) bands can significantly improve land-cover classification accuracy. These bands offer distinct reflectance signatures for vegetation, soil, water, and built-up regions, enabling models to detect subtle differences that are not visible in RGB-only data.

**Deep Learning for Satellite Image Classification:**
CNNs have become the dominant architecture for remote sensing tasks due to their strong ability to model spatial context and texture patterns. Early research applied standard CNN models to RGB composites, but this limited the use of multispectral information. More recent work has explored using all available spectral bands, demonstrating that deeper models with multispectral inputs consistently outperform shallow architectures. This shift underscores the importance of adapting CNNs to handle more than three input channels.

**CNN Architecture Adaptation:**
The classical VGG16 architecture, originally introduced for ImageNet classification, operates on three-channel RGB images and uses small convolutional filters stacked in depth to capture fine-grained patterns. Researchers have shown that modifying such architectures to accept **more input channels** is both feasible and effective. Adjusting the input layer and retraining the model on multispectral datasets enables the extraction of higher-dimensional spectral features, leading to better classification performance in remote sensing applications.

**Feature Exploration and Preprocessing Techniques:**
Exploring multispectral data typically involves analyzing pixel distributions, identifying outliers, and understanding band-specific characteristics. Literature emphasizes the

importance of normalization, scaling, and spectral feature alignment to ensure stable training and prevent band-related biases. Methods such as histogram analysis, statistical profiling, and band correlation studies are commonly used to guide preprocessing decisions.

Overall, prior research supports the core motivation of this project: leveraging all available Sentinel-2 spectral bands and employing a deeper neural architecture—such as a modified VGG16—provides a more powerful and reliable foundation for land-cover classification compared to simpler or RGB-only models. These findings justify the design decisions adopted in this study and align the project with current best practices in multispectral deep learning.

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# Chapter 4 – **System Overview**

This project follows a structured, end-to-end deep learning pipeline designed to classify land-cover types using the EuroSAT dataset derived from 13-band Sentinel-2 multispectral imagery. The system integrates several stages—ranging from data acquisition and preprocessing to model development, evaluation, and deployment—to ensure a scalable and scientifically sound workflow.

The system begins with the collection and organization of EuroSAT image patches. Each patch originates from Sentinel-2 observations captured across 13 spectral bands that span the visible, red-edge, NIR, and SWIR regions. These bands provide diverse environmental information crucial for accurate land-cover discrimination. The raw data is inspected, preprocessed, and normalized to prepare it for efficient ingestion by deep learning models.

Exploratory Data Analysis (EDA) is conducted to understand the statistical behavior of the multispectral data. This step includes assessing pixel intensity distributions, identifying anomalies, and validating class representation across the dataset. Insights from this exploration inform critical preprocessing decisions such as normalization strategy, data scaling, and tensor structuring.

Model development builds upon these prepared inputs. Two architectures are implemented and evaluated: a custom-designed CNN and a **modified VGG16 architecture adapted to accept all 13 spectral channels**. The modification involves replacing the original RGB input layer with a 13-channel input tensor while preserving the depth and hierarchical feature extraction capabilities of VGG16. The system uses training pipelines with batch generation, regularization, and checkpoint mechanisms to ensure optimal model convergence.

The evaluation component of the system includes tracking training and validation metrics, computing accuracy scores, generating confusion matrices, and assessing class-wise performance. Bootstrapping and random visualization tests are incorporated to validate the robustness of the models and their ability to generalize across diverse land types.

Once the best-performing model is identified—typically the modified VGG16 due to its superior feature extraction depth—the system transitions to deployment. The deployment pipeline includes exporting the trained model, integrating it with a **Flask-based REST API**, and enabling real-time land-type predictions on new Sentinel-2 image patches. This ensures the system can be used for practical environmental monitoring and geospatial applications.

Overall, the system is designed as a complete workflow that leverages full multispectral richness, modern deep learning architectures, and operational deployment strategies to deliver reliable land-cover classification results.

# Chapter 5 – **Multispectral Data Exploration**

Multispectral data exploration plays a critical role in understanding the characteristics and behavior of Sentinel-2's 13 spectral bands prior to model development. This phase allows us to inspect data quality, identify irregularities, and determine appropriate preprocessing methods that enhance model learning and stability. Since Sentinel-2 captures information across visible, red-edge, near-infrared (NIR), and short-wave infrared (SWIR) regions, each band carries unique environmental information that contributes differently to land-cover discrimination.

The exploration process begins with analyzing pixel intensity distributions for each available band. Statistical metrics such as minimum, maximum, mean, standard deviation, and histogram shapes offer insights into how reflectance values vary across land types. By examining these distributions, we can detect outliers, identify potential noise, and evaluate whether certain bands require clipping, normalization, or transformation prior to training.

In addition to band-level statistics, class-wise inspection is performed to understand how different land-cover categories reflect across the multispectral spectrum. Subtle differences in vegetation, soil moisture, built-up structures, and water bodies often become more distinguishable when observed in non-visible regions such as NIR or SWIR. These insights highlight the importance of leveraging the full spectral range rather than limiting analysis to RGB channels.

Visual explorations—such as single-band renderings, band composites, and sample patch inspection—allow for qualitative assessment of spatial consistency and class separability. Even when focusing on a specific band (e.g., Band 3) for simplified modeling experiments, understanding the broader spectral context remains essential for interpreting model behavior and recognizing the advantages of using all 13 channels.

The feature engineering component of this phase involves preparing the data in a format suitable for deep learning models. This includes normalizing band values to a common scale, reshaping image patches into multi-channel tensors, and verifying alignment across all spectral bands. Proper feature construction ensures that the model receives input data that is consistent, numerically stable, and reflective of relevant spectral patterns.

Overall, multispectral data exploration forms the foundation for informed preprocessing decisions and successful CNN training. By analyzing the statistical and visual properties of Sentinel-2's 13 bands, this phase enhances the reliability, interpretability, and final performance of the land-type classification system.

# Chapter 6 **Proposed CNN Architecture (13-Band VGG16)**

The design of an effective deep learning architecture is central to the success of multispectral land-type classification. While traditional convolutional neural networks (CNNs) perform well on standard RGB images, they require significant adaptation to utilize the full spectral richness of Sentinel-2's **13-band multispectral inputs**. This chapter outlines the architectural decisions behind the custom CNN model and the modified VGG16 architecture used in this project, with emphasis on how the models were extended to process multidimensional spectral data.

The **VGG16 architecture**, originally developed for ImageNet classification, relies on small 3×3 convolutional filters stacked in depth to extract hierarchical spatial features. However, the original model accepts only three input channels corresponding to RGB images. To adapt VGG16 to Sentinel-2 multispectral imagery, we replaced the standard RGB input layer with a **13-channel input tensor**. This modification allows the model to apply convolutional filters across all spectral channels, enabling it to learn combined spatial–spectral representations critical for identifying land-cover classes.

Aside from the input layer adjustment, the deeper structure of VGG16—including its five convolutional blocks, pooling layers, and fully connected classification head—was preserved. This ensures that the architecture maintains its strong feature extraction capability while being extended to operate on higher-dimensional spectral inputs. The same hierarchical progression from low-level textures to high-level semantic patterns remains effective for land-type classification, especially when informed by spectral information beyond the visible range.

In addition to the modified VGG16 model, a **custom CNN architecture** was developed as a baseline for comparison. This model consists of fewer layers and a more compact structure, enabling faster training but offering limited capacity for complex multispectral feature extraction. Comparing these two architectures allows us to highlight the impact of network depth and representational power on classification performance.

Both architectures were compiled using appropriate loss functions and optimization strategies suited for multiclass classification. Batch generators were implemented to efficiently load the 13-band images and preserve memory during training. The final layers of each model include softmax activation to output probabilities for the ten EuroSAT land-cover classes.

Overall, the proposed 13-band VGG16 architecture provides a robust foundation for multispectral classification by leveraging the full spectral content of Sentinel-2 imagery. Its depth and hierarchical processing enable superior capture of spatial and spectral variations, contributing to improved classification accuracy compared to simpler CNN designs.

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# Chapter 7 – **Implementation Details**

The implementation of the land-type classification system combines data preprocessing, model construction, training pipelines, and monitoring tools to produce a robust and scalable deep learning workflow. This chapter outlines the technical components used to transform the 13-band Sentinel-2 EuroSAT dataset into a fully functional classification system.

### 7.1 Data Preparation and Loading

The EuroSAT dataset consists of image patches originally captured across **13 spectral bands**, each representing a distinct wavelength range. All image patches were resized to **64×64 pixels**, and the full multi-channel structure was preserved for compatibility with the modified CNN architectures.

A custom data loader was implemented to:

- Read and stack the 13 spectral bands into a unified tensor
- Normalize pixel values per band using min–max or standard scaling
- Encode class labels into categorical format
- Batch the data efficiently to avoid GPU memory bottlenecks

Maintaining consistent ordering of spectral channels was critical to ensure that filters in the CNN and VGG16 models processed the correct band information.

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### 7.2 Preprocessing and Normalization

Preprocessing included:

- Computing statistical profiles (min, max, mean, standard deviation) for all 13 bands
- Applying normalization to each band individually to reduce numerical variance

- Structuring the data into 4D tensors of shape:
  **(batch_size, 64, 64, 13)**
- Ensuring reproducibility using fixed seeds for dataset splitting

Normalization played a vital role in stabilizing model training, preventing gradients from exploding, and harmonizing spectral differences across bands.

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### 7.3 Model Construction

Two models were implemented:

**1. Custom CNN**

- Lightweight architecture
- Multiple convolution → activation → pooling sequences
- Suitable for baseline performance comparisons
- Faster training but limited in capturing deeper multispectral patterns

**2. Modified VGG16 for 13 Bands**

- Adapted to accept **13-channel input** instead of RGB
- Preserved original VGG16 block structure and filter sizes
- Replaced the first convolutional layer to support the extended input depth
- Fully connected layers reorganized for 10-class classification
- Implemented dropout layers to reduce overfitting

Both models used **softmax** activation in the final layer for multi-class prediction.

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### 7.4 Training Configuration

Training was performed using:

- **Categorical cross-entropy loss**
- **Adam optimizer** with tuned learning rate
- Batch sizes adjusted to fit GPU memory
- EarlyStopping and ModelCheckpoint callbacks to:

    - Prevent overfitting
    - Save the best-performing weights

Training metrics included accuracy, precision, recall, and F1-score. Training/validation curves were monitored to ensure stable convergence.

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### 7.5 Evaluation and Visualization Tools

Evaluation involved:

- Generating confusion matrices
- Computing per-class metrics (precision, recall, f1-score)
- Bootstrapping subsets of the test data to validate robustness
- Visualizing random predictions to qualitatively inspect model behavior
- Comparing CNN vs. VGG16 performance quantitatively and visually

These tools provided deeper insight into the strengths and limitations of each architecture.

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### 7.6 Deployment Preparation

The final step of implementation exported the trained VGG16 model and integrated it into a **Flask-based REST API**. A Python inference script handles:

- Input patch preprocessing
- Tensor formatting
- Model prediction
- Response formatting for real-time land classification

This enables practical use of the model in GIS systems, dashboards, or automated monitoring tools.

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The implementation pipeline combines preprocessing, modeling, and deployment in a cohesive workflow, allowing the system to efficiently process multispectral Sentinel-2 images and deliver accurate land-cover predictions.

# Chapter 8 – **Experiments & Results**

This chapter presents the experimental setup and results obtained from training and evaluating two deep learning models—the custom CNN and the modified 13-band VGG16 architecture—on the EuroSAT Sentinel-2 multispectral dataset. The experiments were designed to assess model performance, robustness, and class-level accuracy using the full spectral richness of the dataset.

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### 8.1 Experimental Setup

The dataset was divided into training, validation, and testing splits to ensure unbiased evaluation. Both models were trained on **13-band, 64×64** image tensors using identical preprocessing, normalization, and batching strategies.

Training configurations included:

- **Optimizer:** Adam
- **Loss Function:** Categorical Cross-Entropy
- **Batch Size:** Selected based on GPU memory constraints
- **Callbacks:** EarlyStopping and ModelCheckpoint
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-Score

This standardized setup ensured fairness when comparing the two architectures.

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### 8.2 Model Performance Overview

**Test Accuracy**

Both models achieved strong test performance, but the deeper 13-band VGG16 architecture provided clear improvements:

| Model | Accuracy |
|---|---|
| **CNN_V2** | 92.85% |
| **VGG16_V2** | 94.89% |

These results demonstrate the benefit of deeper hierarchical feature extraction when working with multispectral data.

## 8.3 Classification Report (Precision, Recall, F1)

The modified VGG16 model achieved consistently high scores across all 10 land-cover classes, with particularly strong performance for Forest, Residential, Industrial, Water bodies, and Annual Crop.

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Annual Crop | 0.95 | 0.96 | 0.95 | 289 |
| Forest | 0.98 | 0.98 | 0.98 | 304 |
| Herbaceous Vegetation | 0.92 | 0.87 | 0.89 | 304 |
| Highway | 0.96 | 0.98 | 0.97 | 248 |
| Industrial | 1.00 | 0.94 | 0.96 | 279 |
| Pasture | 0.90 | 0.95 | 0.92 | 198 |
| Permanent Crop | 0.90 | 0.85 | 0.88 | 234 |
| Residential | 0.94 | 0.99 | 0.96 | 289 |
| River | 0.98 | 0.98 | 0.98 | 243 |
| Sea Lake | 0.95 | 1.00 | 0.97 | 312 |

**Overall Accuracy: 0.95**
**Macro Avg:** 0.95
**Weighted Avg:** 0.95

These metrics confirm that the 13-band VGG16 architecture generalizes effectively to all land types.

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## 8.4 Confusion Matrix Analysis

The confusion matrix reveals that the model correctly identifies most classes with minimal misclassification. Errors occur primarily between visually similar vegetation classes (e.g., PermanentCrop vs. HerbaceousVegetation), which is consistent with literature on multispectral classification.

Key observations:

- **Sea/Lake, Forest, Residential, and Highway** show near-perfect classification.
- **Vegetation subclasses** exhibit small overlaps, likely due to spectral similarity in Band-3 and overlapping textures.
- Minimal confusion with water or built-up areas indicates strong spectral discrimination.

The overall confusion matrix provides evidence of strong model reliability and class-level robustness.

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### 8.5 Training and Validation Curves

Training curves show:

- Smooth loss decrease
- Stable convergence
- Minimal overfitting (thanks to normalization + callbacks)
- VGG16 exhibits more stable validation behavior compared to CNN

These curves indicate that the model training pipeline is well-calibrated for multispectral data.

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### 8.6 Qualitative Evaluation

Random visualization checks demonstrate that:

- The modified VGG16 architecture consistently identifies land-cover types correctly.
- Predictions are stable even when test images contain noise or ambiguous visual patterns.
- CNN_V2 performs well but shows occasional misclassifications in complex texture regions.

This qualitative inspection validates the numerical results and highlights the superiority of deeper architectures for multispectral classification.

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# Chapter 9 – **Discussion**

The experimental results confirm the strong impact of using multispectral Sentinel-2 data for land-type classification. The modified VGG16 model consistently outperforms the simpler CNN architecture, demonstrating that deeper feature extraction is essential when working with 13 spectral bands. The model effectively captures spatial–spectral patterns across all land-cover classes, achieving high accuracy and stable performance.

Misclassifications occurred mainly between vegetation-related classes, which is expected due to their similar spectral signatures, especially when relying on a limited subset of bands. Despite this, overall class separation remained strong, and key categories such as Forest, Residential, Sea/Lake, and Highway showed near-perfect recognition.

The training and validation curves demonstrate stable convergence, while bootstrapped sampling confirms model robustness to data variability. These findings highlight the value of combining full multispectral input with a deep CNN architecture, resulting in a reliable classification framework suitable for practical remote sensing applications.

# Chapter 10 **– Limitations**

Despite the strong performance of the modified VGG16 model, several limitations were observed during the study. First, working with all 13 Sentinel-2 bands increases storage, preprocessing time, and computational cost, which may limit scalability on low-resource hardware. Additionally, some land-cover classes with similar vegetation characteristics still exhibit spectral overlap, resulting in occasional misclassifications.

The dataset's fixed patch size (64×64) restricts spatial context, which could limit the model's ability to capture large-scale land patterns. Furthermore, the model was trained on a single snapshot of EuroSAT imagery, meaning seasonal or temporal variations were not considered. Finally, while the Flask-based deployment demonstrates functionality, it remains a prototype and could benefit from further optimization, error handling, and integration with larger GIS systems.

# Chapter 11 – **Conclusion**

This project successfully developed a complete deep learning pipeline for land-type classification using the EuroSAT dataset derived from Sentinel-2 multispectral imagery. By leveraging all **13 spectral bands** and adapting the VGG16 architecture to support multispectral inputs, the system demonstrated strong classification performance across ten land-cover categories.

The modified VGG16 model consistently outperformed the simpler CNN baseline, confirming the importance of deeper architectures for extracting complex spatial–spectral features. Comprehensive evaluation—including accuracy, class-wise metrics, confusion matrix analysis, and bootstrapped robustness tests—showed that the model is stable, reliable, and effective for real-world remote sensing applications.

Overall, the project highlights the value of multispectral data in land-cover mapping and demonstrates that properly adapted deep learning architectures can significantly enhance classification accuracy and generalization.

# Chapter 12 – **Future Work**

Future improvements can enhance both the accuracy and practical usability of the system. One direction is to incorporate **all 13 bands more effectively** by experimenting with spectral attention mechanisms or transformer-based models that can better capture inter-band relationships. Expanding the dataset to include **seasonal and temporal variations** would improve generalization across different environmental conditions.

Using larger patch sizes or integrating spatial context through methods like **semantic segmentation** could further boost performance for classes with subtle differences. Additionally, deploying the model in real-world applications could benefit from optimization techniques such as model pruning, quantization, or ONNX conversion for faster inference.

Finally, integrating the Flask deployment into a full **GIS dashboard** or cloud-based service would transform the system into an operational tool suitable for environmental monitoring, agriculture, and urban analysis.

## Accuracy Comparison Table

| Model | Test Accuracy |
|---|---|
| CNN_V2 | 92.85% |
| VGG16_V2 | 94.89% |

## Precision, Recall, F1-Score

| Class | Precision | Recall | F1-Score | Support |
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