Land Type Classification

A Deep Learning Approach Using EuroSAT Sentinel-2 Imagery

Meet the Team

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The Challenge: Unlocking Insights from Satellite Data

Accurate Land Classification

Essential for environmental monitoring, agriculture, and urban planning. High-resolution classification informs critical decisions.

Complexity of Multispectral Data

Multispectral data offers rich information, but effectively processing it to extract meaningful features is a significant hurdle.

Limited Spectral Input

Building a robust model capable of learning complex land-cover patterns using only Band 3 presents a unique deep learning challenge.

Our goal is to develop an efficient, reliable, and deployable land-type classification pipeline using deep learning techniques.

Project Workflow Overview

Our project follows a structured five-milestone approach, ensuring comprehensive development and robust results.

01

Data Collection, Exploration, and Preprocessing

Gathering and preparing the EuroSAT dataset for model training.

02

Model Development and Training

Designing and training our deep learning architecture for land classification.

03

Model Optimization and Performance Tuning

Refining the model to achieve optimal accuracy and efficiency.

04

Real-Time Model Deployment and Visualization

Implementing the trained model for practical, real-world application.

05

Final Documentation and Presentation

Summarizing our findings, methodology, and project outcomes.

EuroSAT Dataset: A Foundation for Classification

We leverage the EuroSAT dataset, a powerful resource for land-use and land-cover classification from Sentinel-2 imagery.

The EuroSAT dataset, sourced from Kaggle, comprises Sentinel-2 multispectral images, specifically designed for land-use and land-cover classification tasks. Each image is originally composed of **13 spectral bands**, covering visible, Near-Infrared (NIR), and Short-Wave Infrared (SWIR) wavelengths.

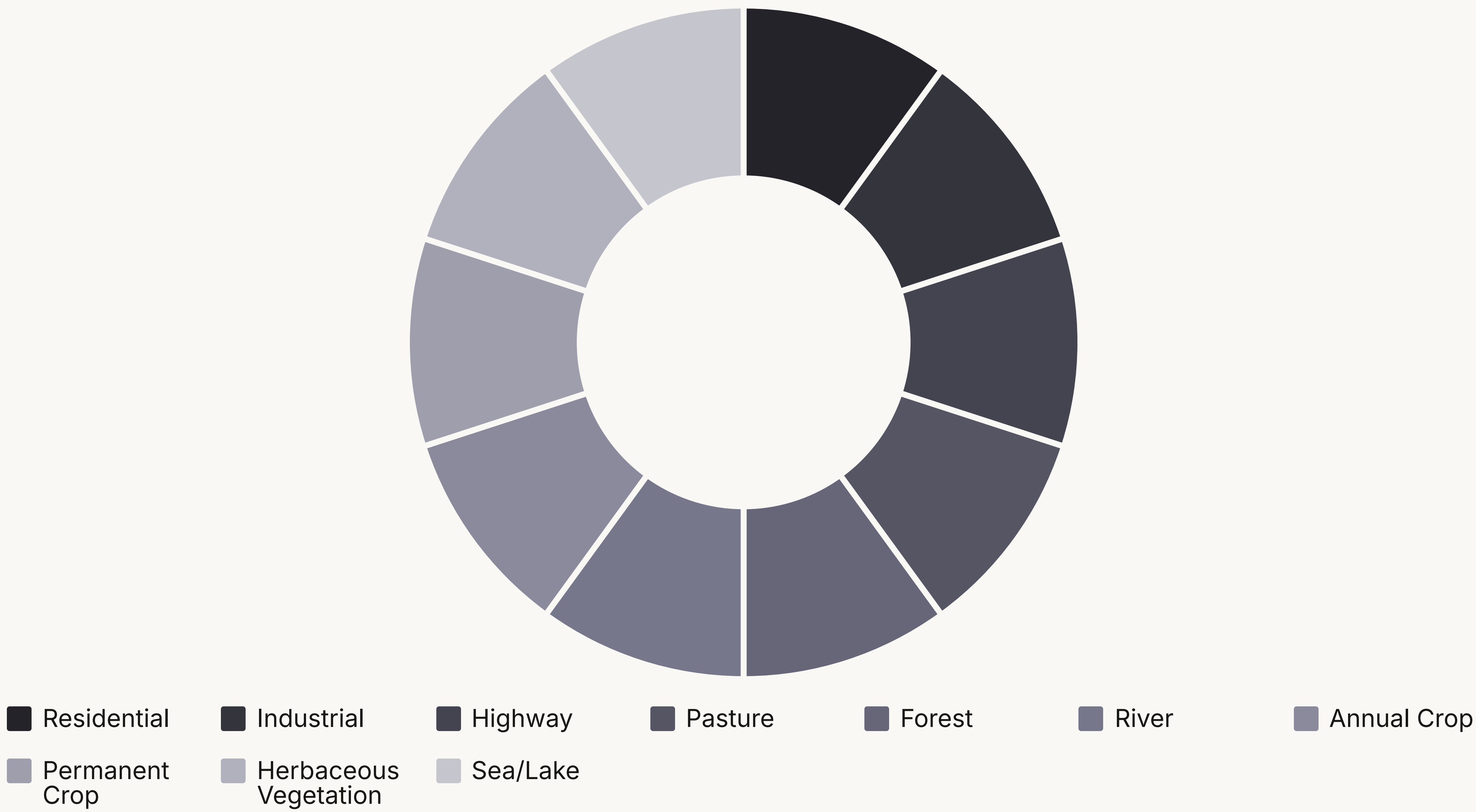
For this project, we specifically focus on **Band 3** (visible spectrum), simplifying the analysis while still capturing critical land-cover information. All images are consistently resized to **64x64 pixels** for uniform processing.

10 Land-Cover Classes

- Residential
- Industrial
- Highway
- Pasture
- Forest
- River
- Annual Crop
- Permanent Crop
- Herbaceous Vegetation
- Sea/Lake

Phase 1: Data Preparation - Ensuring Class Balance

A balanced dataset is crucial for preventing model bias and ensuring robust, stable training, especially when working with limited spectral information.



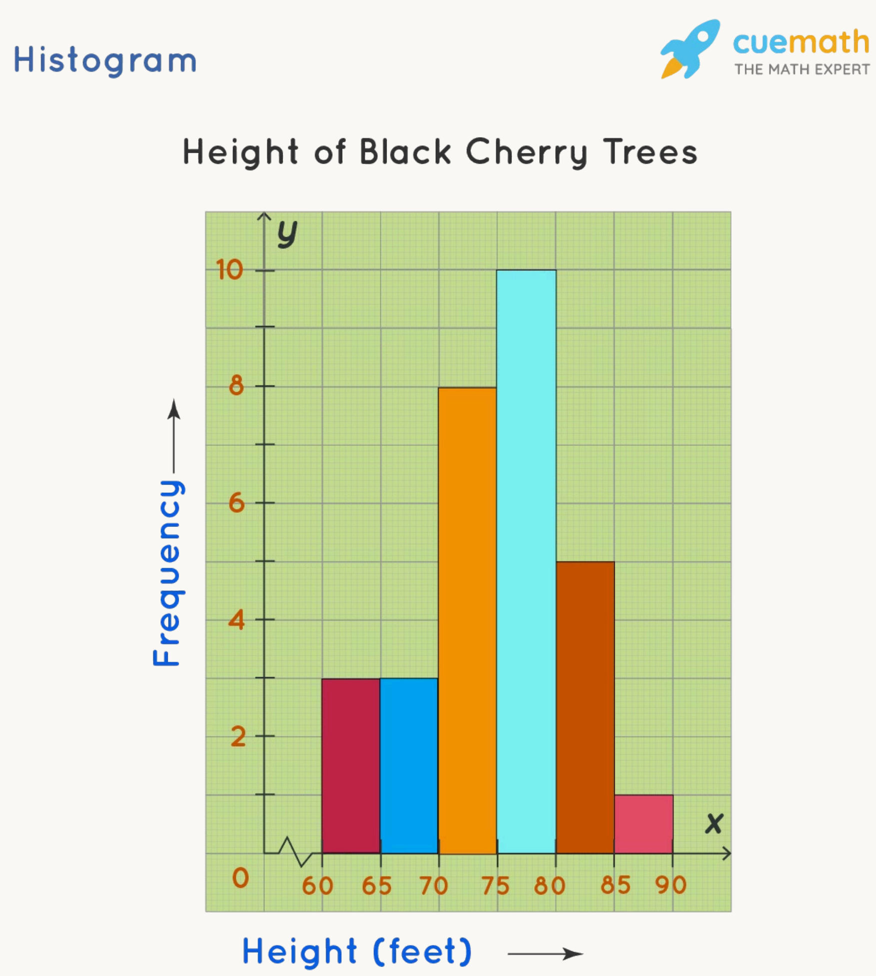
- The EuroSAT dataset features 10 classes with a balanced distribution, each containing a similar number of samples.
- This balanced nature is critical for preventing model bias and ensuring consistent performance across all land types.
- Data is meticulously split into training, validation, and test sets to facilitate effective model evaluation.
- Maintaining class balance is particularly important when training deep learning models on a single spectral band, ensuring every class receives adequate representation during the learning process.

Phase 2: EDA & Feature Building

Exploratory Data Analysis (EDA)

Our EDA process meticulously examines the characteristics of Band 3 images.

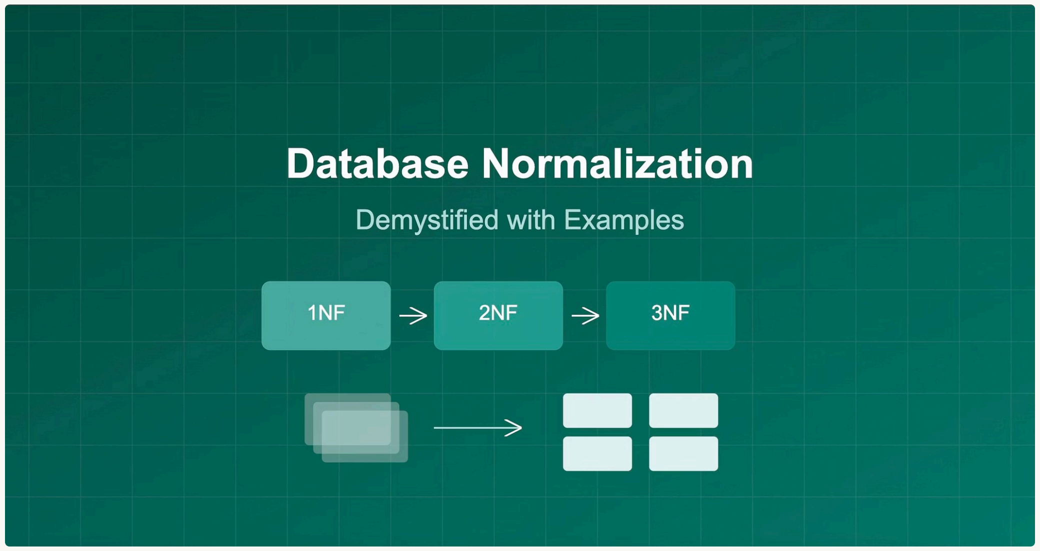
- Analyzing pixel intensity distributions to understand value ranges and common patterns.
- Identifying outliers that might affect model performance.
- Investigating inter-class differences to highlight distinctive features for each land type.
- Utilizing histograms and descriptive statistics to capture the inherent behavior of Band 3 data.



Feature Building

Feature engineering transforms raw pixel data into a format suitable for deep learning models.

- Applying normalization to standardize pixel values, improving training stability.
- Scaling data to optimize performance and convergence rates.
- Structuring data into appropriate tensors for input into convolutional neural networks.
- These insights directly guide preprocessing decisions, enhancing model stability and predictive power.



Phase 3: Model Training with Modified VGG16

We adapted the powerful VGG16 architecture to effectively learn from our single-channel Band 3 satellite imagery.

Modified VGG16 Architecture

Adapted from a 3-channel RGB input to a single-channel Band 3 input, maintaining its deep feature extraction capabilities.

Model Compilation & Setup

Configuring loss functions, optimizers, and batch generators to efficiently process the dataset during training.

Optimal Weight Selection

Utilizing Model Checkpoint and Early Stopping callbacks to save the best performing weights and prevent overfitting.

Performance Monitoring

Continuous monitoring of accuracy and loss curves provides real-time insights into the model's learning progress.

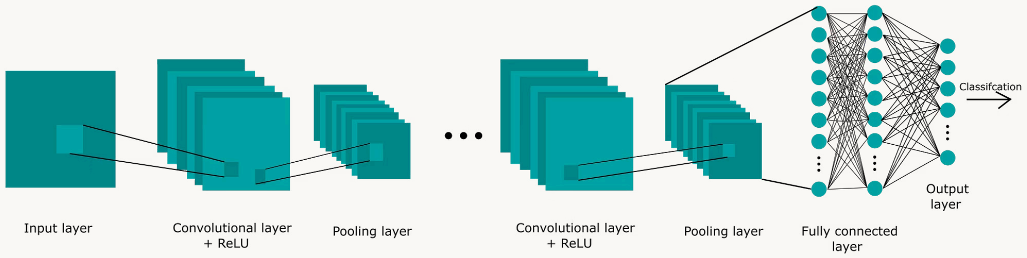
Our objective is to achieve robust learning of spatial-spectral patterns, maximizing classification accuracy for diverse land types.

Performance Comparison: Simple CNN vs. Modified VGG16

The deeper Modified VGG16 architecture demonstrates superior performance for complex land-type classification.

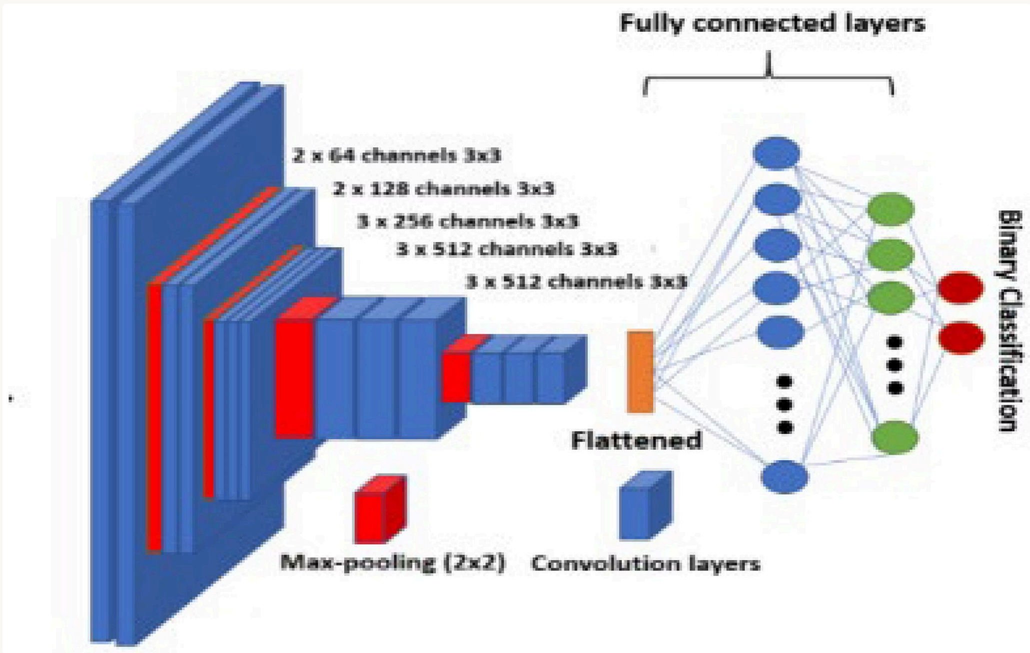
Simple CNN

- **Fewer Layers:** Faster training times due to less computational complexity.
- **Limited Feature Extraction:** Effective for basic patterns but struggles with intricate spatial signals in satellite imagery.
- **Applicability:** Suitable for simpler classification tasks or preliminary analysis.



Modified VGG16

- **Deeper Architecture:** Enables stronger, more hierarchical feature extraction.
- **Single-Band Adaptation:** Successfully customized for Band 3 input, retaining VGG16's power.
- **Superior Metrics:** Achieves significantly higher accuracy, precision, recall, and F1-score.
- **Stable Training:** Exhibits more consistent and stable training behavior, leading to reliable results.



Key Takeaway: The Modified VGG16 significantly outperforms the simple CNN, providing a more accurate and robust solution for land-type classification from Sentinel-2 Band 3 data.

Performance Comparison: Simple CNN vs. Modified VGG16 cont.

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CNN_V2 Test Accuracy: 0.9285185185185185
VGG16_V2 Test Accuracy: 0.9488888888888889
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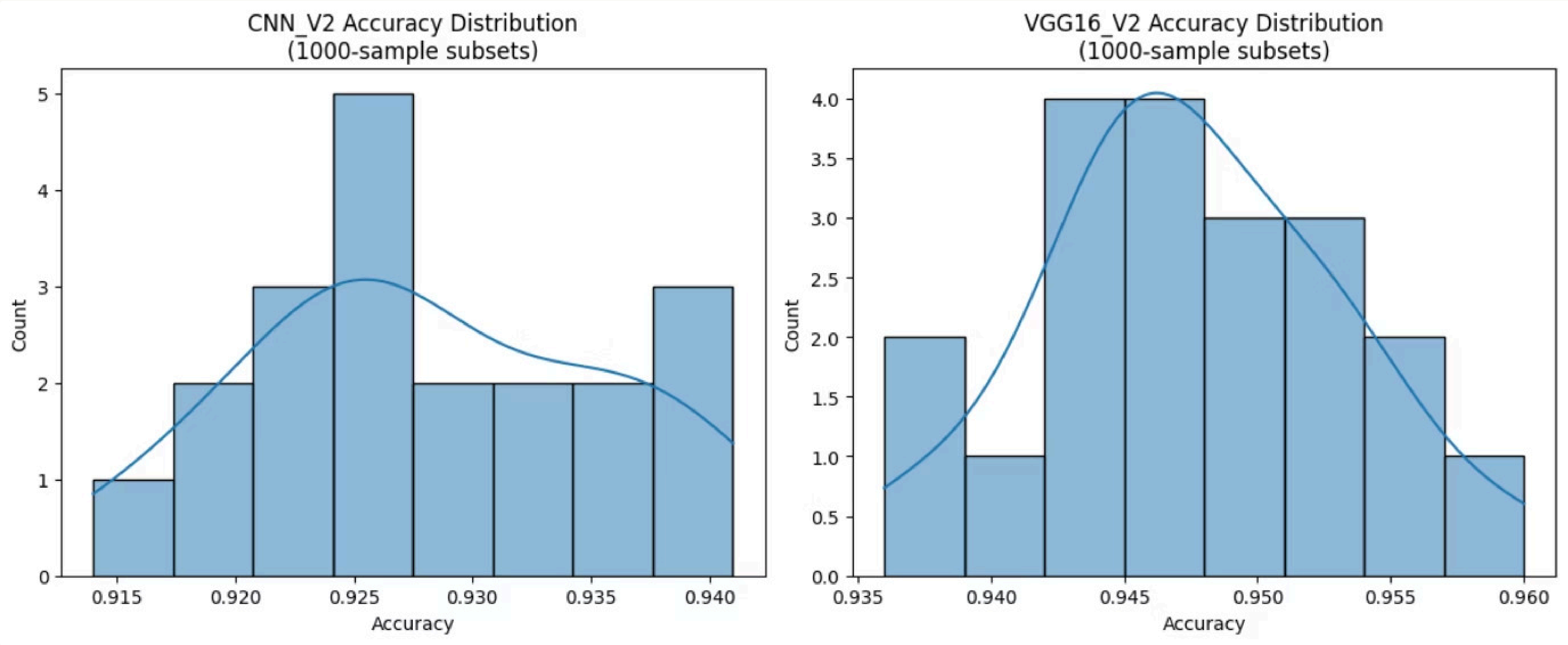
Our evaluation results reveal a clear performance difference between the two architectures.

The enhanced **Modified VGG16** model achieved a higher **Test Accuracy of 94.89%**, outperforming the **CNN_V2** model, which reached **92.85%**.

This improvement reflects VGG16's deeper feature extraction capability and its ability to learn more complex spatial patterns from the input imagery, even when using a single spectral band (Band 3).

The results demonstrate that a deeper architecture provides stronger generalization and more reliable land-type classification performance.

Reliability



Model Performance Summary (CNN_V2 vs VGG16_V2)

- **VGG16_V2 consistently outperforms CNN_V2** when trained on the 13-band Sentinel-2 dataset.
- Both models achieve **high test accuracy (>92%)**, demonstrating strong generalization.
- **VGG16_V2 reaches ~95% accuracy**, reflecting its deeper feature extraction capability.
- **Bootstrapped sampling** shows stable performance across multiple random subsets, confirming model robustness.
- **Random visualization checks** indicate that both models correctly classify the majority of land-cover types, even in complex scenes.

Key Insight:

The deeper VGG16_V2 architecture provides more reliable and accurate predictions, making it the preferred model for land-type classification.

Deployment: Bringing the Model to Life

Deploying our trained model allows for automated, scalable land-cover classification in real-world applications.

Model Export

The trained deep learning model is exported into a deployable format, ready for inference on new Band 3 satellite images.

Deployment Options

The model was deployed through a **Flask REST API**, enabling real-time prediction and seamless integration with GIS or monitoring dashboards.

Scalability & Integration

Focus is placed on scalability, ensuring low-latency predictions, and seamless integration with existing Earth observation workflows.

This final phase enables real-time insights and automated decision-making across various environmental and planning sectors.