

Landslide Detection Using Deep Learning and Multispectral Satellite Images

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Table of Contents

- 1 Introduction
- 2 Previous Work
- 3 Dataset Preparation
- 4 Methodology
- 5 Class Imbalance Handling

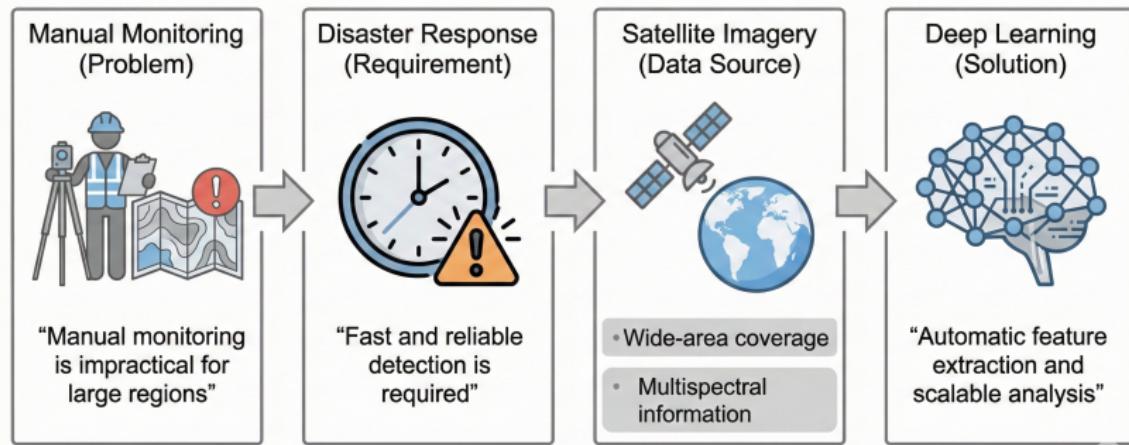
Problem Statement



- Landslides are among the most destructive natural disasters.
- They cause severe loss of:
 - Human life
 - Infrastructure
 - Natural resources

Need for Automation

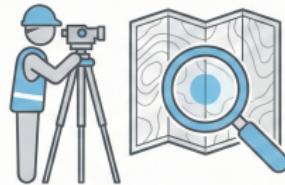
Need for Automation



- Manual monitoring is impractical for large geographical regions.
- Disaster response requires fast and reliable detection.

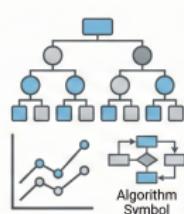
Previous Work

Evolution of Landslide Detection Methods



Manual Methods (Early Work)
Manual surveys and visual interpretation

Traditional Machine Learning



Traditional Machine Learning
SVM, Random Forest, Logistic Regression

Deep Learning Approaches



- CNNs (feature learning)
- ResNet, DenseNet
- U-Net (pixel-level segmentation)

Present Day

- Landslide detection methods evolved from manual surveys to machine learning and deep learning approaches.
- Deep learning models enable automatic and robust feature learning compared to traditional methods.

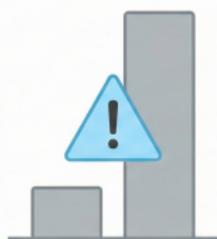
Limitations of Previous Work

- Severe class imbalance in landslide datasets.
- Deep models overfit due to limited landslide samples.
- Underutilization of multispectral satellite data.
- Bias in fully connected classifiers.

Need for Improvement

Need for Improvement in Landslide Detection

Class Imbalance Handling



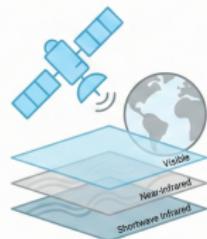
Explicit handling of class imbalance is required

Generalization Across Regions



Better generalization across different geographical regions

Multispectral Information Utilization



Effective use of multispectral satellite data

- Existing methods lack effective class imbalance handling and generalization.
- Improved utilization of multispectral data is essential for robust landslide detection.

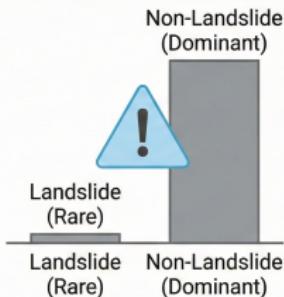
Dataset Description

- Multispectral satellite dataset from **Zindi Africa**.
- Acquired via Landslide Detection competition.
- Each sample:
 - 64×64 pixels
 - 12 spectral bands
 - Stored in .npy format
- Two classes: Landslide and Non-landslide.

Challenges in the Dataset

Challenges in the Dataset

Class Imbalance



Highly imbalanced class distribution between landslide and non-landslide samples

Visual Similarity



Landslide regions appear visually similar to bare soil and rocky areas

Noise and Environmental Effects



Noise introduced by vegetation cover and atmospheric conditions

- The dataset suffers from class imbalance, visual ambiguity, and environmental noise.
- These challenges motivate robust data balancing and deep feature learning approaches.

Methodology Overview

- Input multispectral satellite images.
- Preprocessing and normalization of raw data.
- Handling class imbalance using offline SMOTE.
- Creation of a balanced training dataset.
- Deep feature extraction using EfficientNetV2-Large.

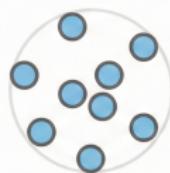
Class Imbalance Problem

- Landslide datasets are highly imbalanced in nature.
- Non-landslide samples significantly outnumber landslide samples.
- This imbalance leads to:
 - Biased learning toward majority class
 - Poor representation of landslide regions
- Addressing class imbalance is essential before training deep models.

Offline SMOTE for Dataset Balancing

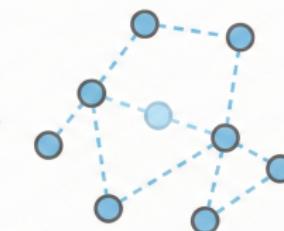
Offline SMOTE for Dataset Balancing

Minority Class Samples (Input)



Landslide samples

Nearest Neighbor Interpolation



Synthetic samples generated in feature space using nearest neighbors

Balanced Dataset (Output)

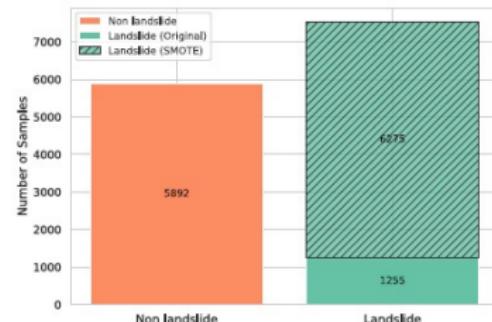
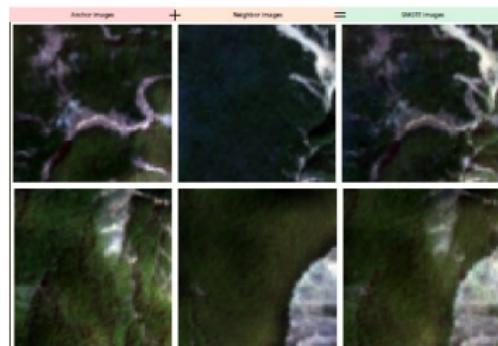


Majority Class

Increased minority samples without duplication

- SMOTE generates synthetic landslide samples by interpolating between nearest neighbors.

Balanced Dataset for Feature Learning



- After applying SMOTE, landslide and non-landslide classes are better balanced.

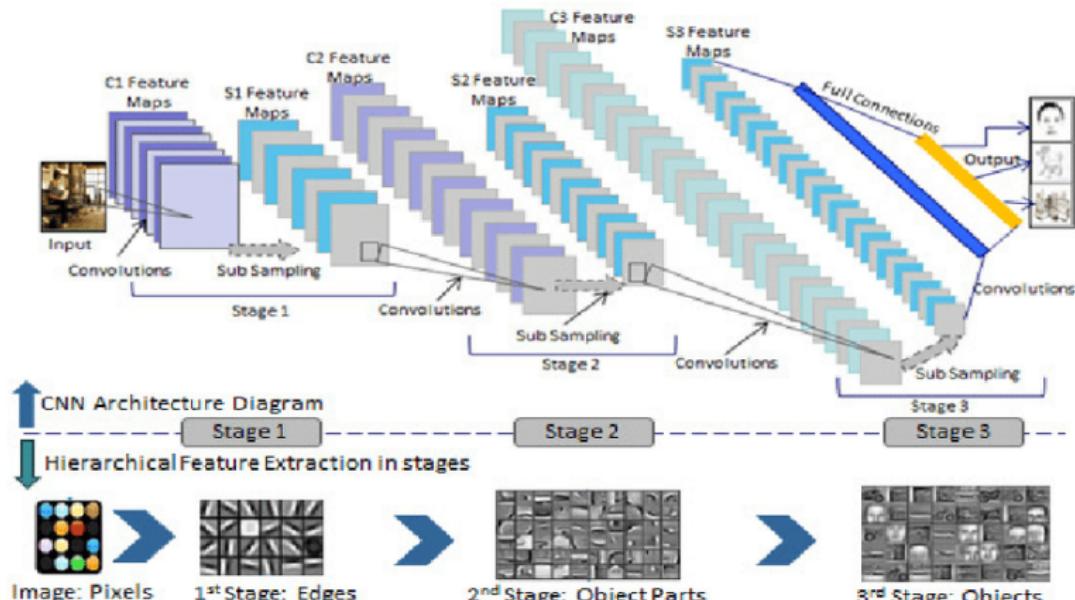
Feature Extraction

- Feature extraction transforms raw multispectral images into meaningful representations.
- Deep features are automatically learned from data without manual design.
- Extracted features capture:
 - Spatial information such as texture and shape
 - Spectral information from multiple satellite bands
- These features are more robust than traditional handcrafted features.

Why CNNs for Feature Extraction

- Convolutional Neural Networks (CNNs) are well-suited for image-based tasks.
- CNNs learn hierarchical features:
 - Low-level features: edges and textures
 - Mid-level features: regions and patterns
 - High-level features: semantic representations
- Local connectivity and weight sharing improve generalization.

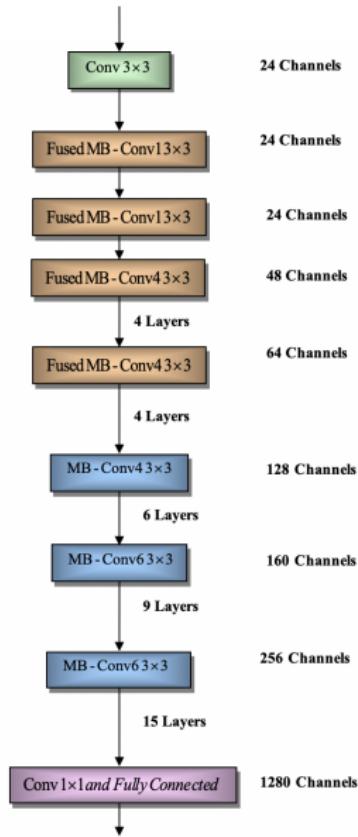
CNN Feature Hierarchy



EfficientNetV2 Architecture Overview

- EfficientNetV2 is a modern and efficient deep convolutional architecture.
- It follows a compound scaling strategy to balance:
 - Network depth
 - Network width
 - Input resolution
- Designed for faster training and improved accuracy.
- Uses Fused-MBConv and MBConv blocks for efficient feature learning.

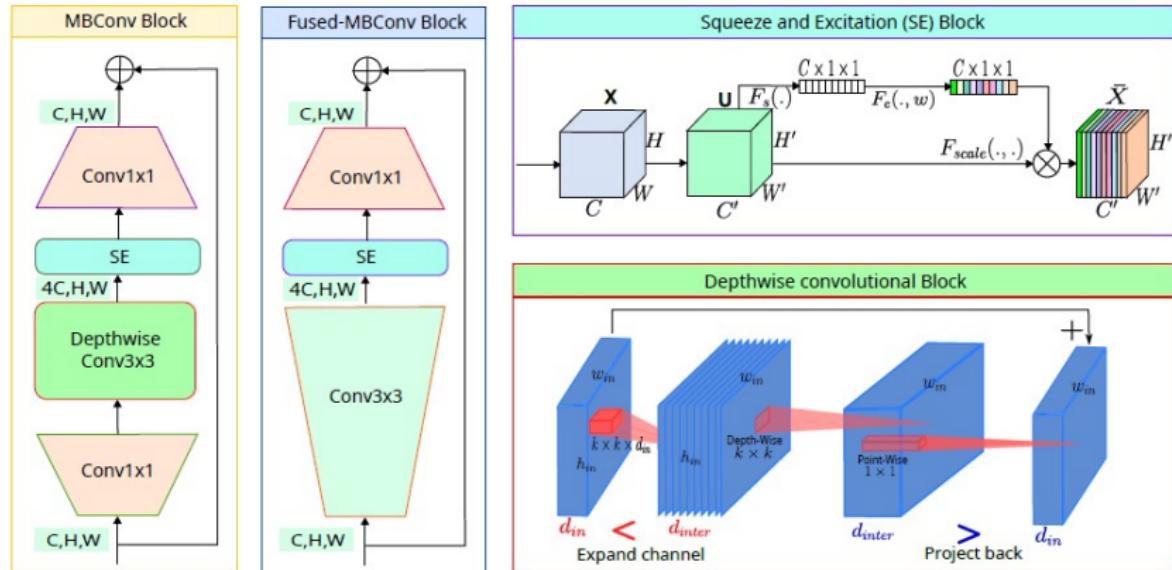
EfficientNetV2 Architecture



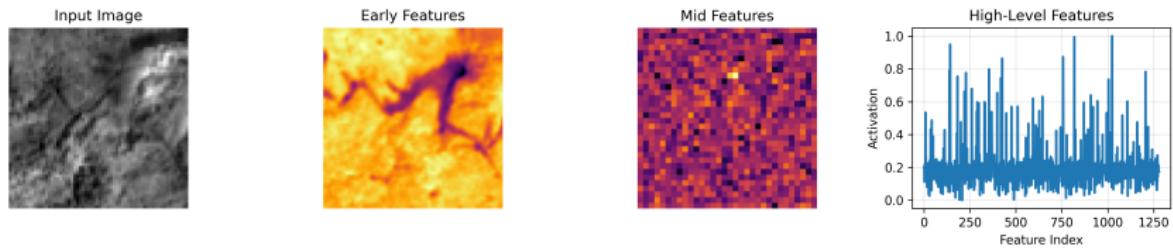
EfficientNetV2 for Multispectral Feature Extraction

- Original EfficientNetV2 is designed for 3-channel RGB images.
- In this work, the input layer is modified to support:
 - 12-channel multispectral satellite images
- Enables effective utilization of terrain, vegetation, and soil information.
- EfficientNetV2 acts as a robust deep feature extractor for landslide detection.

EfficientNetV2-Large Architecture



Feature Extraction Process Visualization



*Step-wise visualization of feature extraction in EfficientNetV2: Input multispectral image
→ Early convolutional features → Intermediate abstract features → High-level feature embedding*

Explanation of Feature Extraction Stages

- **Input Image:**

- Represents a multispectral satellite patch used for landslide detection.
- Contains terrain and surface information across multiple spectral bands.

- **Early Feature Maps:**

- Capture low-level patterns such as edges, textures, and local intensity variations.
- Useful for identifying abrupt terrain changes.

- **Mid-Level Feature Maps:**

- Learn higher-order spatial structures and region-level patterns.
- Encode combinations of textures and terrain characteristics.

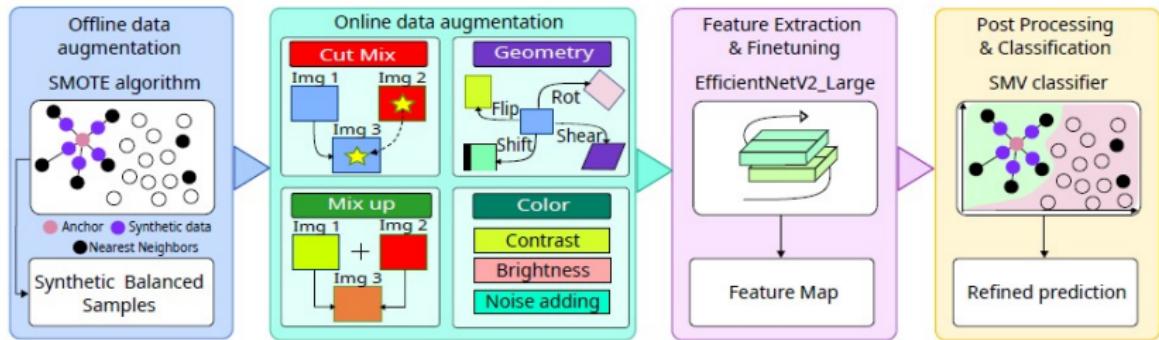
- **High-Level Feature Embedding:**

- Obtained after global pooling in EfficientNetV2.
- Produces a compact feature vector used for final classification.

Feature Extraction Summary

- Multispectral images are processed using EfficientNetV2-Large.
- The network learns discriminative spatial and spectral features.
- Extracted deep features form the foundation for subsequent classification.
- This stage completes the core representation learning of the framework.

High-Level Framework



Work Completed So Far

- Studied the problem of landslide detection using satellite imagery.
- Reviewed existing literature and identified limitations of prior methods.
- Collected and analyzed multispectral satellite dataset from Zindi Africa.
- Performed dataset understanding and identified class imbalance issues.
- Designed the overall deep learning framework.
- Implemented feature extraction using EfficientNetV2-Large:
 - Adapted the network for 12-channel multispectral input
 - Extracted high-level spatial and spectral features
- Completed the core representation learning stage of the project.

Future Work

- Train the deep learning model with optimized hyperparameters.
- Integrate Support Vector Machine (SVM) for final classification.
- Perform extensive performance evaluation using:
 - Accuracy, Precision, Recall, F1-score
- Analyze results and compare with existing approaches.
- Prepare final documentation and presentation.