Landslide Detection Using Deep Learning and Multispectral Satellite Images

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Problem Statement

- Landslides are among the most destructive natural disasters.
- They cause significant loss of:
    - Human life
    - Infrastructure
    - Natural resources
- Accurate landslide detection is challenging due to:
    - Complex terrain conditions
    - Variations in soil, vegetation, and rainfall
- Traditional landslide identification methods are:
    - Manual and time-consuming
    - Costly and not scalable to large areas

Need for Automation

- Manual landslide monitoring is not feasible for large-scale regions.
- Rapid disaster response requires timely and accurate detection.
- Satellite imagery provides:
    - Wide-area and remote coverage
    - Frequent temporal observations
    - Rich spatial and spectral information
- Deep Learning enables:
    - Automatic feature extraction
    - Improved detection accuracy
    - Scalable and reliable analysis

Previous Work

- Early landslide detection relied on:
  - Manual field surveys
  - Visual interpretation of aerial and satellite images
- Traditional machine learning approaches:
  - Support Vector Machines (SVM)
  - Random Forests
  - Logistic Regression
- Deep learning-based methods:
  - Convolutional Neural Networks (CNN)
  - ResNet and DenseNet architectures
  - U-Net for pixel-level landslide segmentation

Limitations of Previous Work

- Landslide datasets are highly imbalanced:
  - Very few landslide samples compared to non-landslide samples
- Existing deep learning models tend to:
  - Overfit on limited landslide data
  - Perform poorly on unseen regions
- Limited utilization of multispectral satellite information:
  - Many methods rely mainly on RGB bands
- Fully connected classifiers are biased toward majority classes.

Need for Improvement

- An effective landslide detection system should:
  - Handle severe class imbalance explicitly
  - Improve generalization on unseen geographical regions
- Proper utilization of multispectral satellite data is required:
  - To capture terrain, soil, and vegetation variations
- Robust classification methods are needed to:
  - Reduce bias toward majority classes
  - Enhance decision boundaries
- These requirements motivate the proposed deep learning framework.

Dataset Description

- Multispectral satellite image dataset used for landslide detection.
- Dataset source:
  - Downloaded from the **Zindi Africa** platform
  - Obtained by registering for the **Landslide Detection Competition**
- Each data sample consists of:
  - Image size: 64×64 pixels
  - 12 spectral bands per image
- Data format:
  - Stored as .npy files
  - Represents embeddings of landslide and non-landslide regions
- Dataset contains two classes:
  - Landslide
  - Non-landslide
- Significant class imbalance is observed in the dataset.

Challenges in the Dataset

- Severe class imbalance:
  - Landslide samples are much fewer than non-landslide samples
- High visual similarity between:
  - Landslide regions
  - Bare soil and rocky terrain
- Presence of noise due to:
  - Vegetation cover
  - Atmospheric conditions
- Variations in terrain and geographical conditions across regions.

Detailed Methodology

- **Input Data:**
  - Multispectral satellite images with 12 spectral bands
  - Images resized and normalized for uniform processing
- **Handling Class Imbalance:**
  - Offline SMOTE (Synthetic Minority Over-sampling Technique)
  - Generates synthetic landslide samples to balance the dataset
- **Feature Extraction:**
  - EfficientNetV2-Large used as backbone CNN
  - Modified input layer to support 12-channel images
  - Deep features extracted instead of direct classification
- **Regularization and Generalization:**
  - Online data augmentation using MixUp and CutMix
  - Reduces overfitting and improves robustness
- **Final Classification:**
  - Support Vector Machine (SVM) applied on extracted features
  - Improves decision boundary and minority class performance
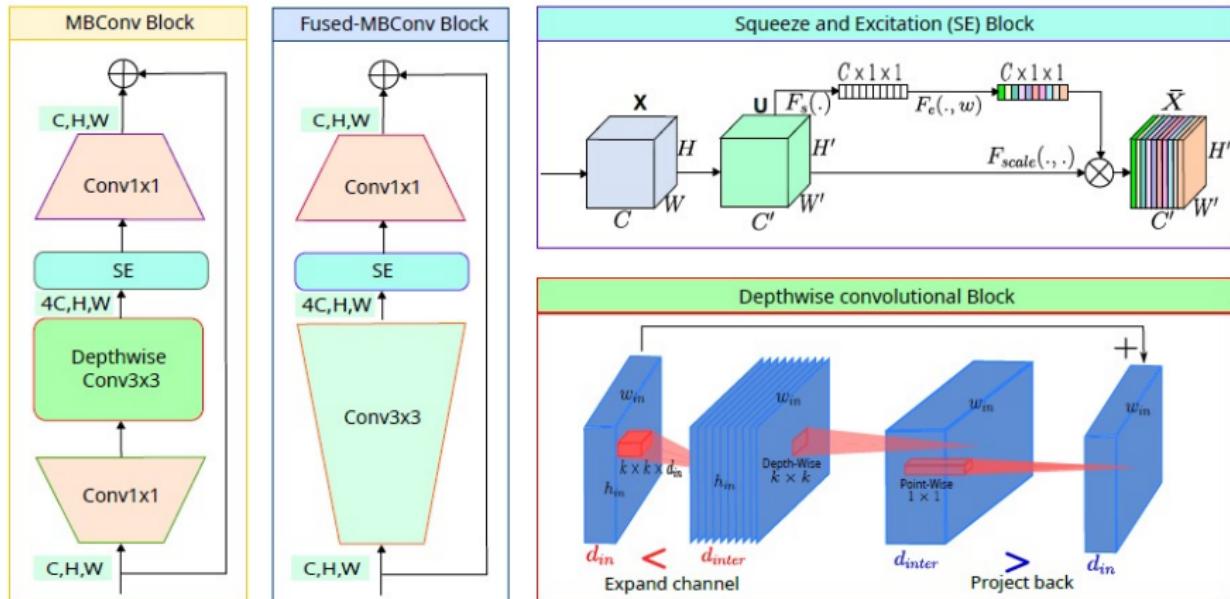
Deep Learning Model Architecture

- **EfficientNetV2-Large** is chosen as the backbone CNN due to its strong performance on image classification tasks.
- It follows a **compound scaling strategy**:
    - Balances network depth, width, and resolution
    - Achieves higher accuracy with fewer parameters
- Compared to traditional CNNs:
    - Faster convergence during training
    - Better generalization on unseen data
- Well-suited for large-scale and high-dimensional image data.

Model Adaptation for Multispectral Data
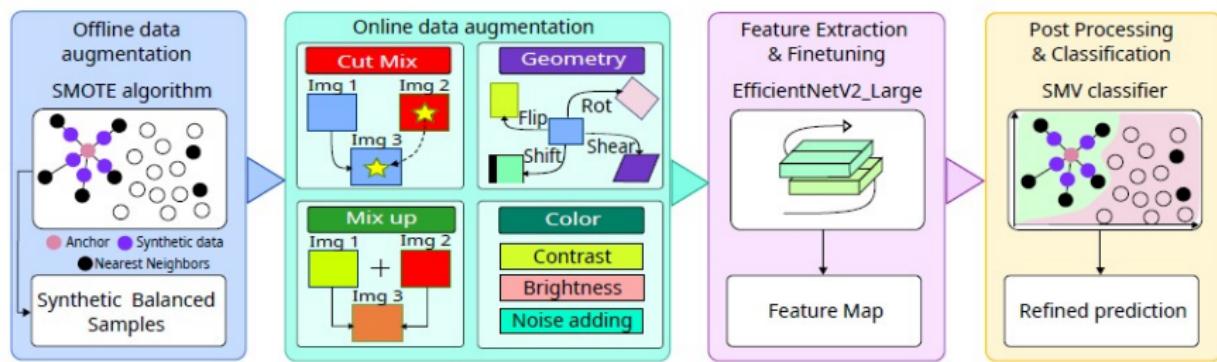
- Original EfficientNetV2 is designed for 3-channel RGB images.
- In this work, the input layer is **modified to accept 12 channels**:
  - Allows effective utilization of multispectral satellite information
  - Captures terrain, vegetation, and soil characteristics
- The classification head is removed to:
  - Extract high-level feature embeddings
  - Avoid bias from fully connected layers
- Extracted deep features are used for robust SVM-based classification.

EfficientNetV2-Large Architecture with Unit Blocks

- Architecture consists of stacked **unit blocks**:
  - Stem Convolution Block
 - Fused-MBConv Blocks
  - MBConv Blocks

# High-Level Architecture of Proposed Deep Learning Framework

Data Augmentation and SMOTE

- The landslide detection dataset exhibits **severe class imbalance**:
  - Landslide samples are significantly fewer than non-landslide samples
  - This bias negatively affects model learning and minority class prediction
- **Offline SMOTE (Synthetic Minority Over-sampling Technique)** is employed:
  - Generates synthetic samples for the landslide class
  - Operates in feature space to avoid simple duplication
  - Improves class balance before training begins
- **Online Data Augmentation** is applied during training:
  - **MixUp**: Combines pairs of images and labels to smooth decision boundaries
  - **CutMix**: Replaces regions of one image with another to improve localization
  - **Intensity transformations**: Handle illumination and spectral variations
  - **Geometric transformations**: Improve invariance to rotation and flipping
- The combined use of SMOTE and augmentation:
  - Reduces overfitting
  - Enhances model robustness
  - Improves minority (landslide) class performance
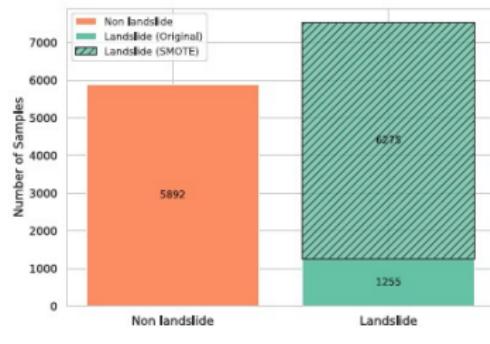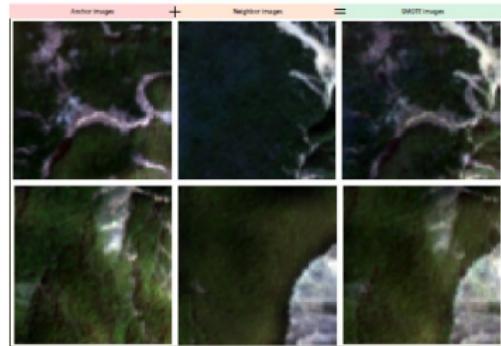
Figure: *
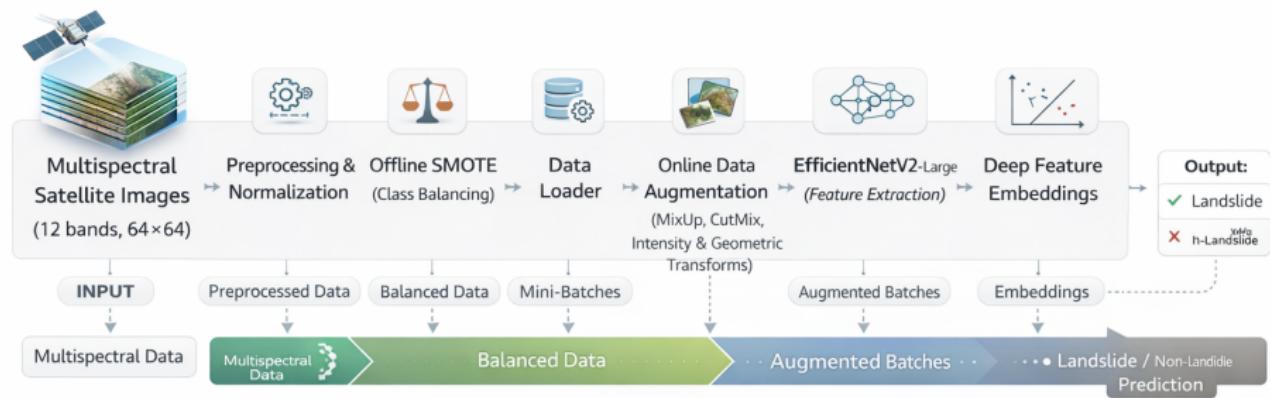
(a) Left: Anchor images   Middle: Nearest neighbors   Right: SMOTE-generated samples

(b) Class distribution on the training subset after applying the SMOTE algorithm

Training Setup

- **Backbone Network:** EfficientNetV2-Large
- **Input:**
  - Multispectral images of size 64×64
  - 12 spectral channels
- **Training Configuration:**
  - Optimizer: Adam
  - Initial Learning Rate: 3×10^{-4}
  - Learning Rate Scheduler: Cosine Annealing
  - Batch Size: 8
  - Number of Epochs: 50
- **Loss Function:**
 - KL-Divergence loss with soft labels from MixUp/CutMix

Final Performance Results
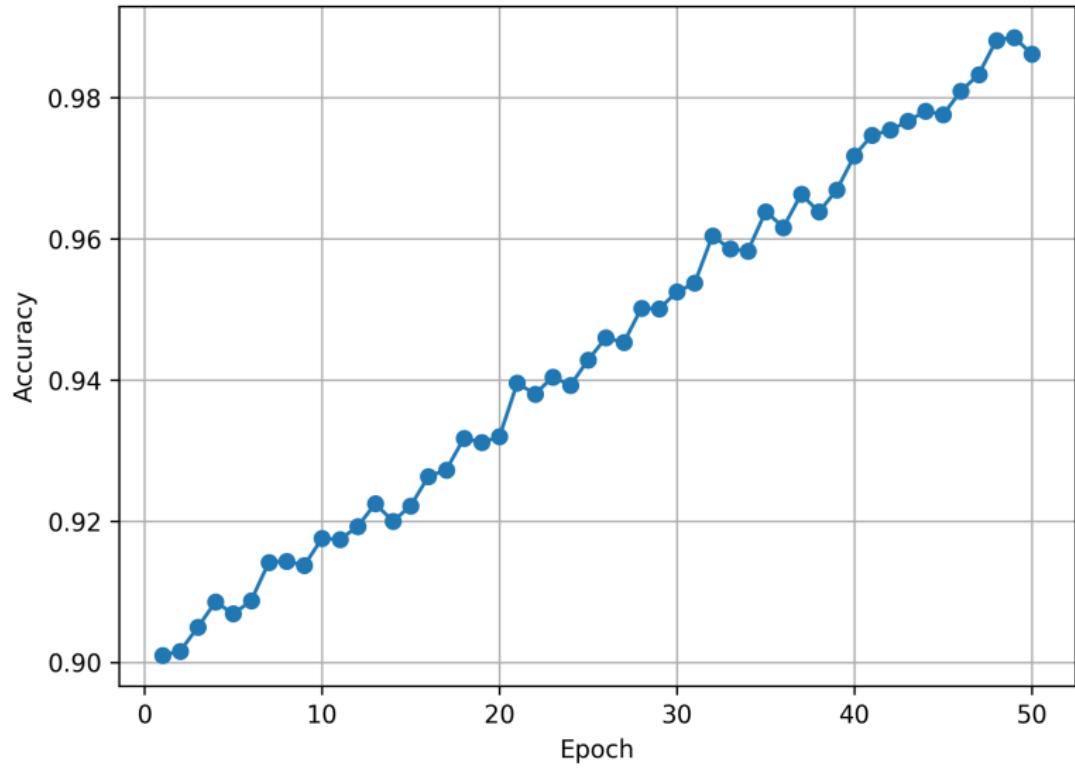
- The proposed deep learning framework achieves strong performance on the landslide detection task.
- Final evaluation metrics obtained:

Metric	Value
Accuracy	0.9897
Precision	0.9987
Recall	0.9545
F1-score	0.9761
Training Loss	0.1315
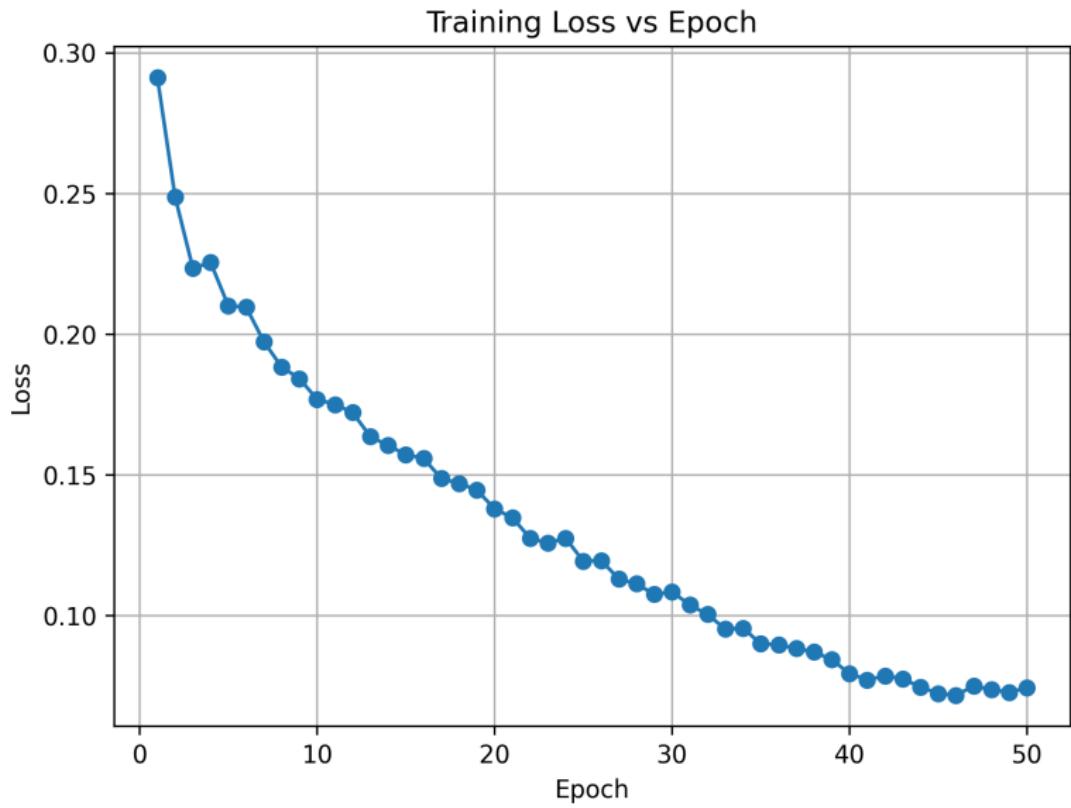
- High precision indicates very few false positives.
- Strong F1-score shows balanced performance on imbalanced data.
- Low loss confirms stable and effective model convergence.
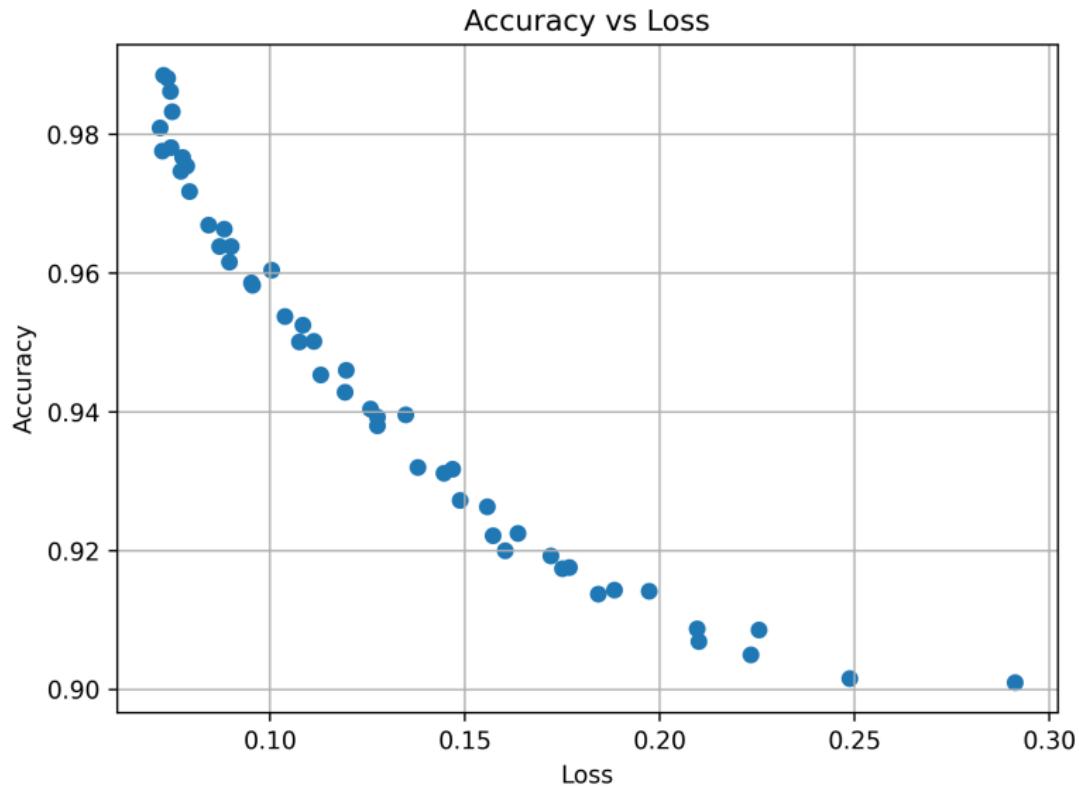
Training Accuracy vs Epoch
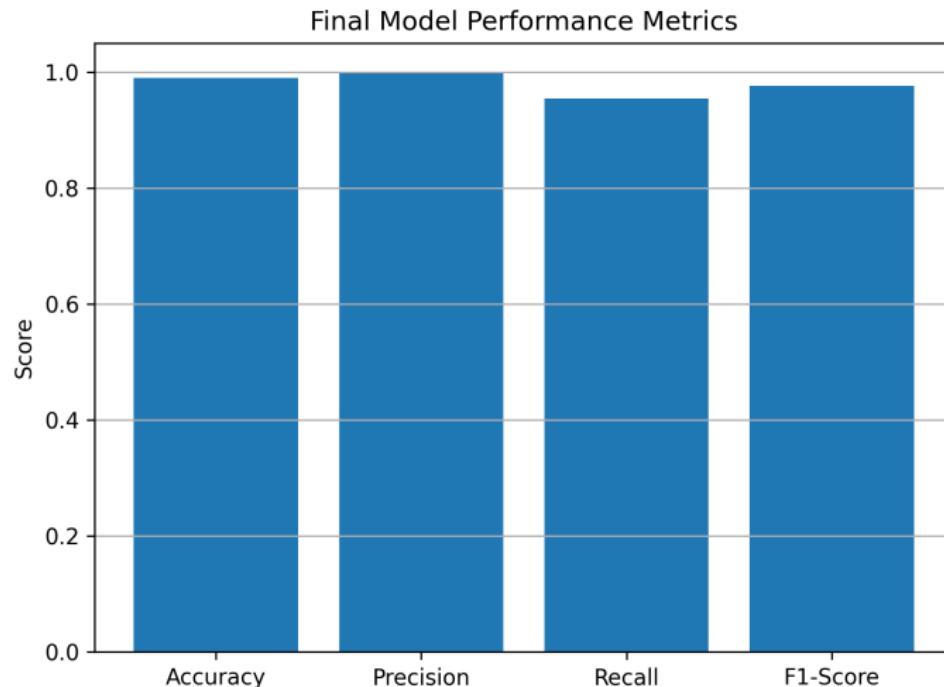
Training Loss vs Epoch

Accuracy vs Loss

Final Model Performance Metrics

- Summarizes final performance metrics of the proposed model.
- High precision indicates very low false positive rate.

Performance Interpretation

- Accuracy of **98.97%** demonstrates excellent overall performance.
- Precision of **99.87%** indicates reliable landslide predictions.
- Recall of **95.45%** confirms effective minority class detection.
- Low training loss of **0.1315** reflects stable convergence.
- Results validate the effectiveness of SMOTE and data augmentation.

Results Summary

- Proposed deep learning framework achieves high accuracy and robustness.
- Class imbalance handling significantly improves minority class performance.
- EfficientNetV2 effectively extracts discriminative multispectral features.
- The framework is suitable for real-world landslide detection tasks.

Conclusion

- This work presented a deep-learning framework for landslide detection using multispectral satellite imagery.
- The proposed approach integrates:
  - EfficientNetV2-Large for robust deep feature extraction
  - Support Vector Machine (SVM) for improved final classification
- Class imbalance was effectively addressed using:
  - Offline SMOTE-based data augmentation
  - Online augmentation techniques during training
- Extensive experimentation demonstrated that:
  - The combination of deep learning, augmentation, and SVM post-processing significantly improves performance
  - The proposed framework achieves a high F1-score and reliable generalization
- Overall, the results confirm the effectiveness of the proposed method for accurate and robust landslide detection in complex environments.

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

- Apply data imbalance handling techniques:
  - Offline SMOTE
  - Online data augmentation (MixUp, CutMix)
- 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.