Report On

An Offline EO Data Processing Challenge
Automatic CLOUD and SHADOW Mask Generation from Resourcesat-2/2A LISS-4 Satellite Images

Registration ID: NRCC251067
Team Members: Bhawuk Arora, Mukul
Institute: Poornima College of Engineering

---

1. Objective

The primary objective of this project is to design and implement an automated and generalized system for the accurate identification and segmentation of cloud and shadow regions in optical satellite imagery. The system uses deep learning techniques and is capable of processing LISS-4 (Resourcesat-2/2A) RGB imagery to generate cloud and shadow masks, and outputs georeferenced raster and shapefile formats for downstream Earth observation applications.

---

2. Dataset Description

- **Source:** Resourcesat-2/2A LISS-4 Georeferenced Level-2 Data
- **Satellite/Sensor:** IRS-R2, L4FX
- **Bands Available:** Red (Band 2), Green (Band 3), NIR (Band 4)
- **Spatial Resolution:** 5.8 meters (native), resampled to 5.0 meters
- **Projection:** UTM, WGS84
- **Format:** GeoTIFF (10-bit DN, 2 Bytes/pixel)
- **Training Samples:** 20 images
- **Test Samples:** 10 (provided for evaluation only)

Preprocessing Pipeline:

1. **Conversion from DN to TOA Reflectance**:
2. Uses sensor-specific gain values (`Lmin`, `Lmax`) for radiance conversion.
3. Sun elevation from metadata to compute zenith angle.
4. Earth–Sun distance from CSV.
5. TOA = (Radiance × π × d^2) / (Esun × cos(θz))
6. **Sun Angle Correction**:
7. Incorporated using the cosine of solar zenith angle to correct irradiance.
8. **Band Normalization**:

9. Images are normalized to [0, 1] for stable training.

10. **Ground Truth Mask Generation**:

11. Semi-automated method using brightness thresholding (Otsu), morphological cleaning, and visual inspection.
12. 3-class labeling: 0 = No Cloud, 1 = Cloud, 2 = Shadow

---

3. Model Architecture / Algorithm Pipeline

Model Used: U-Net

U-Net is a convolutional neural network specifically designed for biomedical image segmentation and is well-suited for pixel-wise classification.

Architecture Summary: - **Encoder Path:** - Conv2D → BatchNorm → ReLU ×2 → MaxPool - Filters: [64, 128, 256, 512]

- **Decoder Path:**
- Upsample (Transposed Conv) → Concatenate Skip Connection → Conv2D ×2

- Filters: [512, 256, 128, 64]

- **Output Layer:**

- Conv2D (1×1 kernel) → 3 Output Classes

Key Details: - **Activation:** ReLU - **Final Activation (Inference):** Softmax - **Loss Function:** CrossEntropyLoss - **Skip Connections:** Allow gradient flow and spatial recovery - **Total Trainable Parameters:** ~31 million

---

4. Training Configuration

- **Framework:** PyTorch
- **Hardware Used:**
- OS: Ubuntu 20.04 / Windows 11
- CPU: Intel i7 (8 cores)
- GPU: NVIDIA RTX 3060 (12GB VRAM)
- RAM: 16 GB

Training Hyperparameters:

- **Loss Function:** CrossEntropyLoss
- **Optimizer:** Adam
- **Learning Rate:** 1e-4
- **Epochs:** 20

- **Batch Size:** 2
- **Validation Split:** 80/20
- **Augmentations:** (Future scope)
- Random flips, brightness variation, small rotations

---

5. Resources Used

Compute Hardware:

- **CPU:** Intel Core i7
- **RAM:** 16 GB
- **GPU:** NVIDIA RTX 3060

Software Stack:

- **OS:** Ubuntu 20.04, Windows 11
- **Key Libraries:**
- `GDAL`, `Rasterio`, `OpenCV`, `scikit-image`
- `NumPy`, `matplotlib`, `geopandas`, `shapely`
- `PyTorch`, `torchvision`, `tqdm`
- `Jupyter Notebook`, `QGIS` (for visualization)

---

6. Evaluation Metrics

a. Classification Metrics:

- **Accuracy**
- **Precision**, **Recall**, **F1-Score** (macro average)
- **IoU** (Intersection over Union)

b. Quantitative Performance (on test set):

Class	Precision	Recall	F1-Score	IoU
No Cloud	0.96	0.97	0.96	0.92
Cloud	0.89	0.87	0.88	0.81
Shadow	0.85	0.84	0.84	0.77
Average	0.90	0.89	0.89	0.83

c. Visual Outputs:

- ✅Predicted mask overlays (Clouds: White, Shadows: Black)
- ✅Shapefile polygons for spatial visualization in GIS tools

- ✅Graphs of training loss, F1-score, IoU

---

7. Analysis

Class-wise Performance:

- **Cloud Detection:** High accuracy due to distinct brightness
- **Shadow Detection:** Slightly lower due to confusion with dark water or terrain

Common Challenges:

- Differentiating snow and clouds in mountainous terrain
- Building shadows sometimes misclassified
- Thin clouds or haze not easily detected in RGB-only imagery

Overfitting/Underfitting:

- Training and validation curves showed no severe overfitting
- Minor oscillation observed in validation IoU due to small dataset size

Potential Improvements:

- Adding Cartosat-1 DEM for topographic shadow correction
- Semi-supervised labeling for improved ground truth masks
- Integration of SWIR-like spectral proxy via synthetic band modeling

---

8. Conclusion and Future Improvements

Summary:

The developed pipeline successfully automates cloud and shadow detection on LISS-4 imagery using an end-to-end U-Net based deep learning framework. All outputs are spatially aligned, georeferenced, and compatible with GIS software for further analysis.

Suitability for Operational Use:

- Can process batch EO scenes with minimal manual intervention
- Generates outputs in both raster and vector format

Limitations:

- RGB-only imagery limits spectral discrimination between haze and bright land
- Model trained on limited samples — generalization improved but can be further boosted

Future Enhancements:

- Add real-time inference capability using ONNX or TensorRT
- Build web-based demo interface for broader usability
- Extend to multitemporal change detection and alerts

♒Final output ready as `.zip` with: - ✅Trained model (`.pth`) - ✅Inference masks and shapefiles - ✅Jupyter notebooks - ✅Documentation & Report

Thank you for the opportunity to participate!