Integration of SAR and Optical Data for Near Real-Time Wildfire Delineation Using a Deep Learning Approach

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Motivation and Goals

- 10m resolution optical data via differenced Normalized Burn Ratio (dNBR) enables wildfire image delineation
- dNBR generates a high number of false positives when affected by weather conditions
- Synthetic Aperture Radar (SAR) is unaffected by weather and yields highly accurate results for pixel-level burned/unburned classification, though relies on significant processing requirements
- Successful integration of dNBR and SAR using deep learning would address the downsides associated with both data sources [2]
- To generate a baseline for comparison, a deep learning model is first trained on the optical data alone

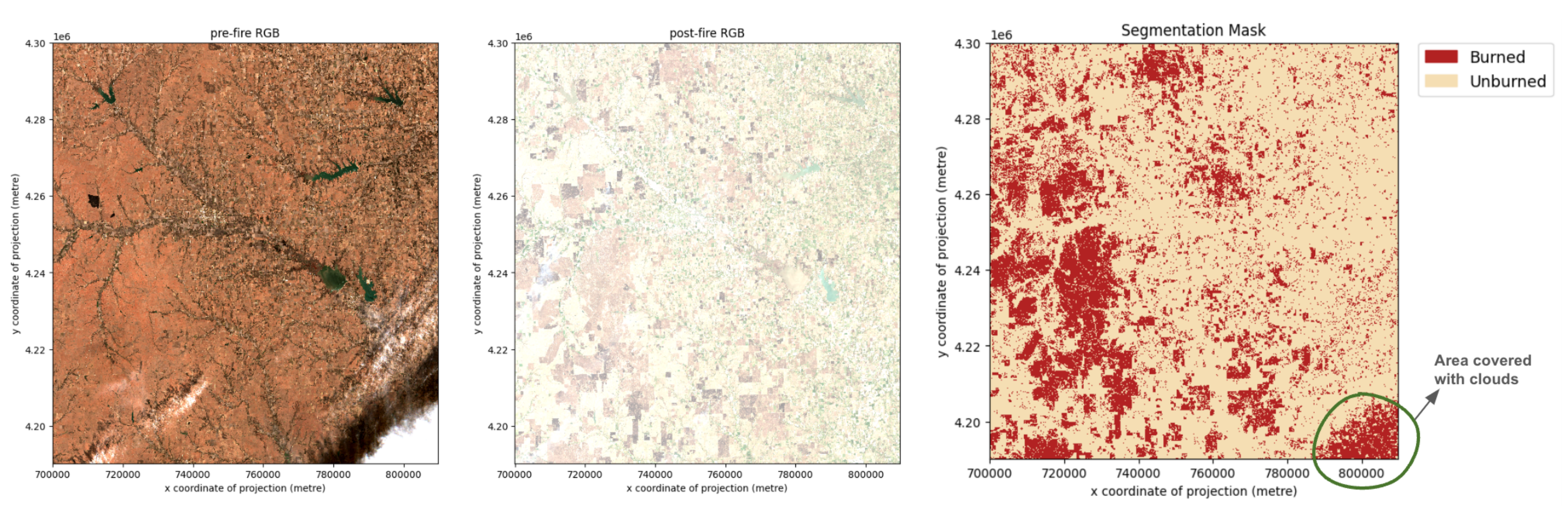

Figure 1. dNBR scenes affected by weather

Dataset

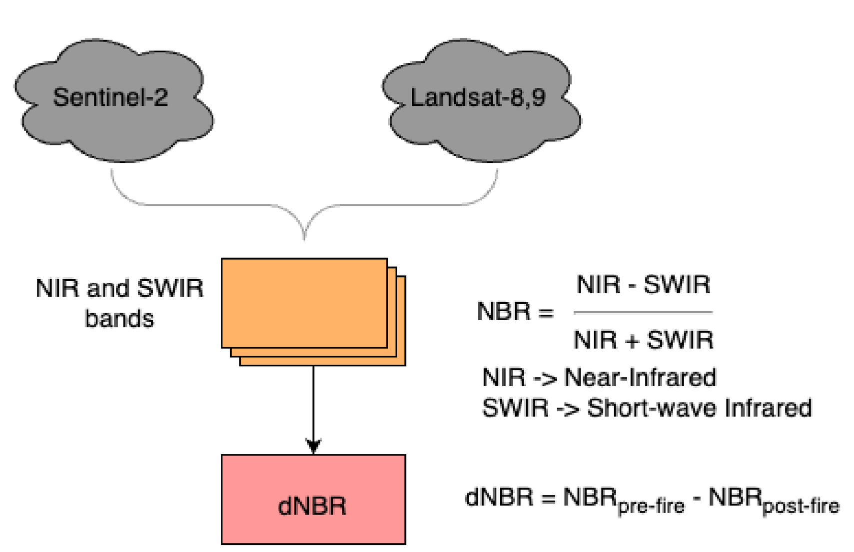

Figure 2. Creating a dataset

- A dataset was created using surface reflectance values from open-source satellite APIs to create dNBR single-band images
- The segmentation masks (ground truth images) were created using a threshold dNBR value of `0.1`, where pixels having a dNBR value of atleast `0.1` were classified as burned areas and pixels with values below `0.1` were classified as unburned areas
- The dataset consists of 1253 images from 20 fires at 10m spatial resolution and image size (10980, 10980) for Sentinel-2 and (21000, 21000) after resampling for Landsat-8/9

Methodology

- For model training, 8 fires (250 images) were used - 6 fires (200 images) for training and 2 fires (50 images) for validation.
- Each image was converted into n equal sized patches of size (256,256) using a patchify layer as seen in Figure 3
- The training was distributed across 3 NVIDIA GeForce GTX 1080 Ti using a batch size of 3
- A pre-trained model, DeepLabV3+, was used by customizing both the input layer to accept a single band input, and the output layer to produce a pixel-wise class prediction for burned or unburned area

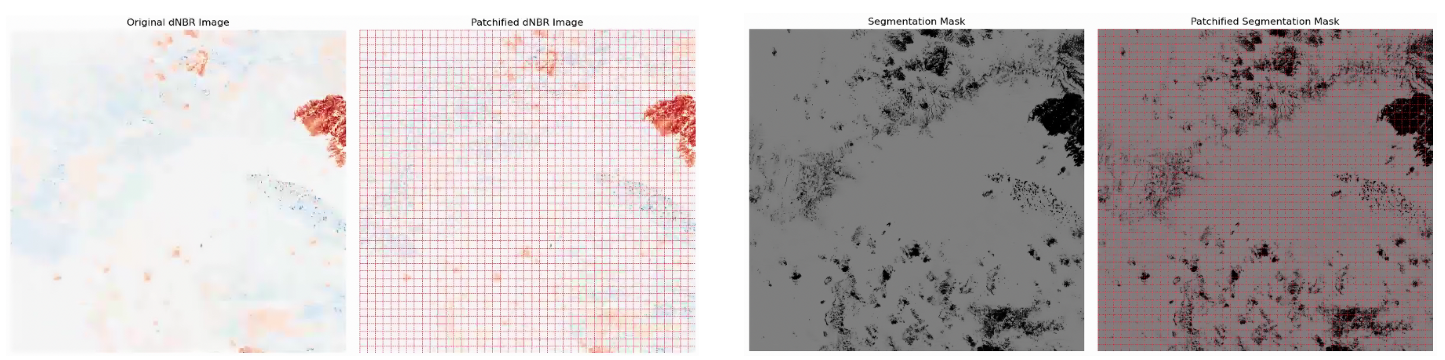

Figure 3. Converting images to patches

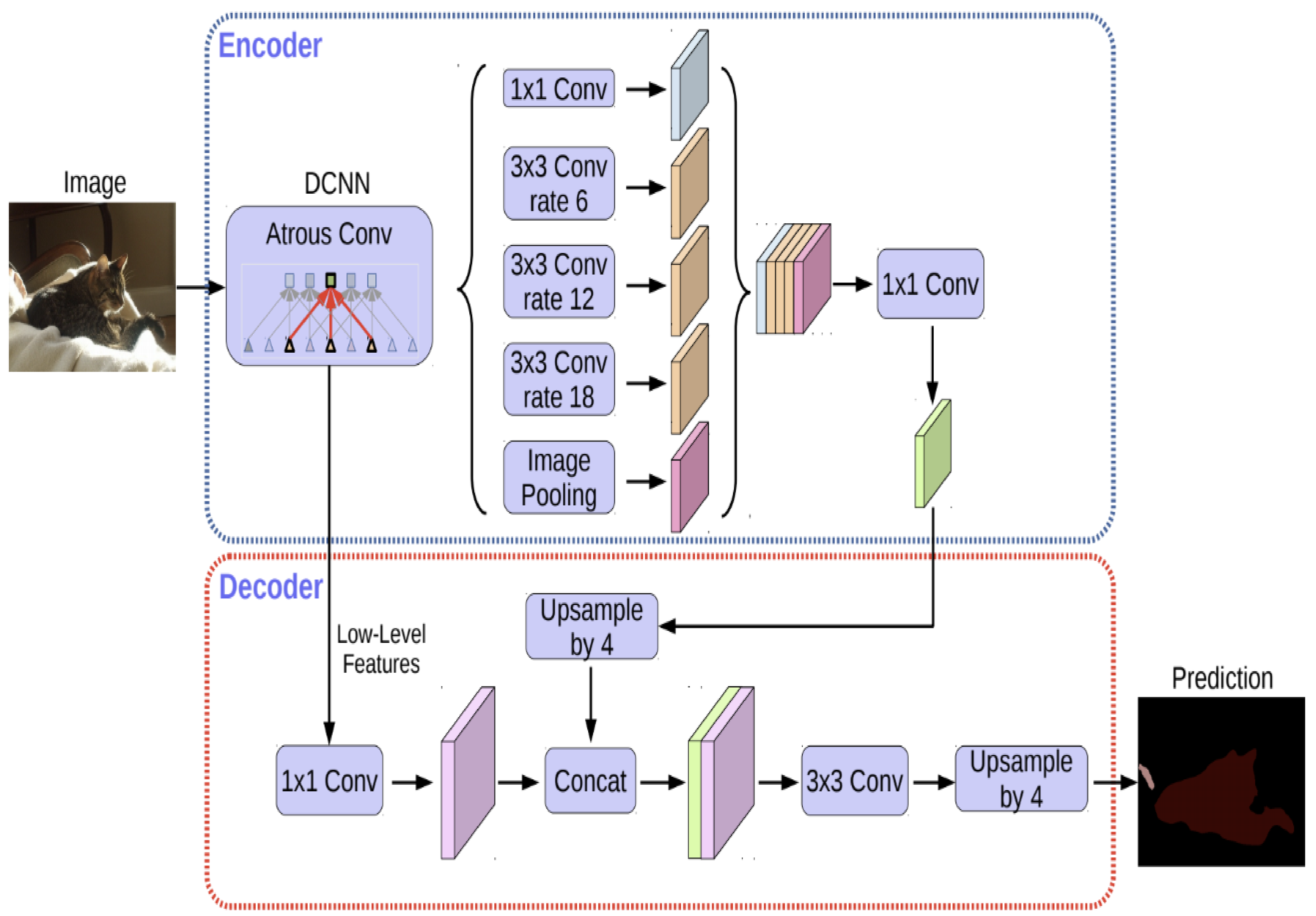

Figure 4. DeepLabV3+ Model Architecture

DeepLabV3+ is a state-of-the-art model for semantic segmentation [1]. It uses an encoder-decoder structure to extract features and upsample them. It is capable of capturing multi-scale contextual information and segmenting images of different resolutions.

Evaluation

Cross-entropy loss and Intersection over Union (IoU) were used to evaluate the model.

No. of classes

$$H(p, q) = -\sum \mathbf{p}(x) \log \mathbf{q}(x)$$

True probability distribution Predicted probability distribution

Figure 5. Cross entropy loss function

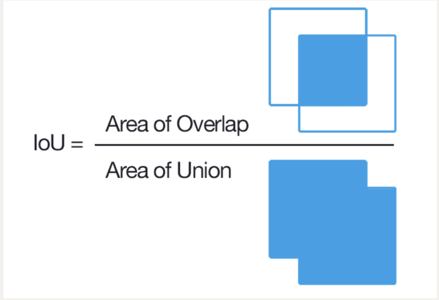

Figure 6. Intersection over Union (IoU)

$$\text{IoU} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives} + \text{False Negatives}} \quad (1)$$

Figure 7. IoU formula

Figure 8. Evaluation metrics

Cross entropy loss and IoU together address accuracy and correct overlap of predictions, i.e., it emphasises correct predictions being made in correct locations within the image.

Average Test loss = 0.14 Average Test IoU = 0.76

Next Steps

- Train the model using dice coefficient loss function for improved boundary mapping of burned/unburned regions//
- With evidence of model suitability, re-train using SAR change detection as the segmentation mask (ground truth), paving way for a more direct baseline for SAR-optical integration
- Fuse SAR and optical data into a single data structure for combined model training

References

[1] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *Proceedings of the European conference on computer vision (ECCV)*, pages 801–818, 2018.

[2] Daniela Stroppiana, Ramin Azar, Fabiana Calò, Antonio Pepe, Pasquale Imperatore, Mirco Boschetti, João MN Silva, Pietro A Brivio, and Riccardo Lanari. Integration of optical and sar data for burned area mapping in mediterranean regions. *Remote Sensing*, 7(2):1320–1345, 2015.

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