Automatic landcover change detection and classification from Satellite images

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Abstract

The goal of the project is to build a deep learning model to automate landcover change detection using high resolution satellite imagery over Kigali region of Africa in 2016 and 2019. Three classes i.e. Water, Tree Canopy and Land are chosen for this exercise. Relevant data has been extracted, preprocessed and used to train UNET & FCN architectures for segmentation and land cover change detection tasks

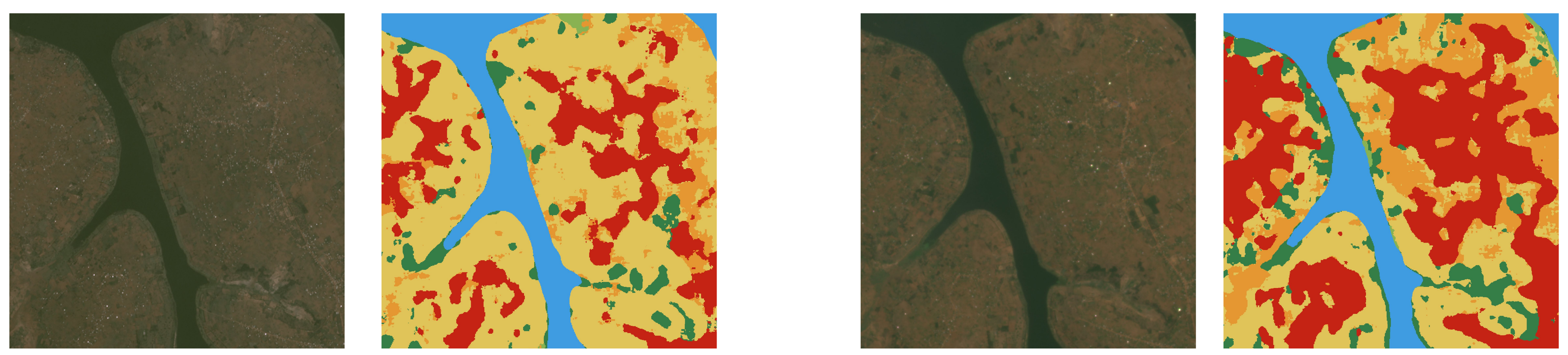
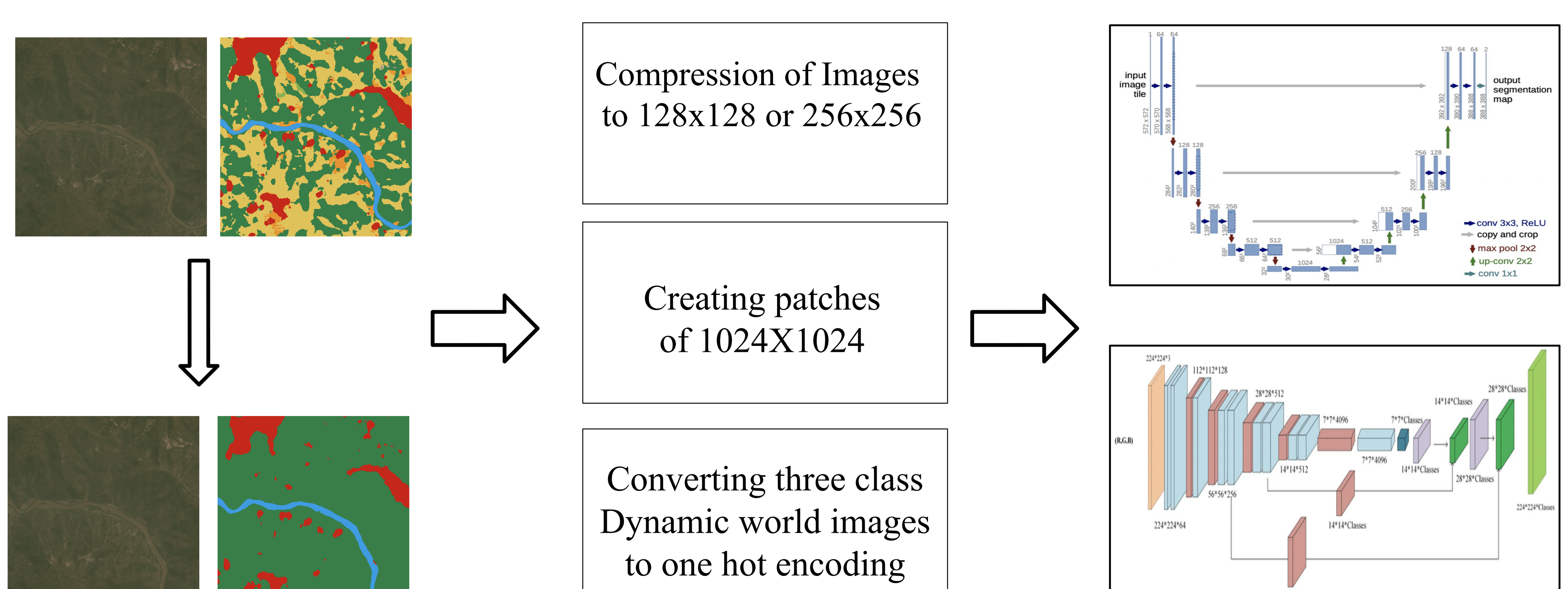


Figure 1. Satellite image and Dynamic world labels of 2016 (L) & 2019 (R)

Methodology

1. Data Extraction and Cleaning: The first step in the process is data extraction of NICFI images (satellite images) and DWL (segmentation masks) using GEE. Multiclass DWL masks are converted to three class masks as per problem statement
2. Data preprocessing: Due to memory limitations, we used data compression and creating patches of the high resolution images to train the model. Also, the segmentation masks are converted to one hot encodings by filtering the pixel values
3. Data Modelling: Following architectures are experimented for modeling
   a. U-net: This architecture has two components, encoder which takes input image and generates low dimensional feature map and a decoder which decomposes feature map to generate the higher dimensional output image
   b. FCN: They employ solely connected layers, such as convolution and pooling



Data Extraction & Cleaning   Data Preprocessing   Data Modelling

Figure 2. Flow Chart of the methodology used from creating data to modelling

* The following image architectures are for reference, the trained models have different architectures with similar base.

Results

For semantic segmentation/predicting land class labels we experimented with FCN and UNet with different backbones and image input methodologies. All the models have been compared against a baseline model and the comparison results are shown in Fig 3. UNet with InceptionV2 backbone and using 1024 patches performs the best with an overall IOU score of 66% which is 37% better than the baseline Neural Network model.

Landcover change: The best model is chosen to detect land cover change over time.

Fig 4 shows tree class that has been lost and gain shows land class gained over time.

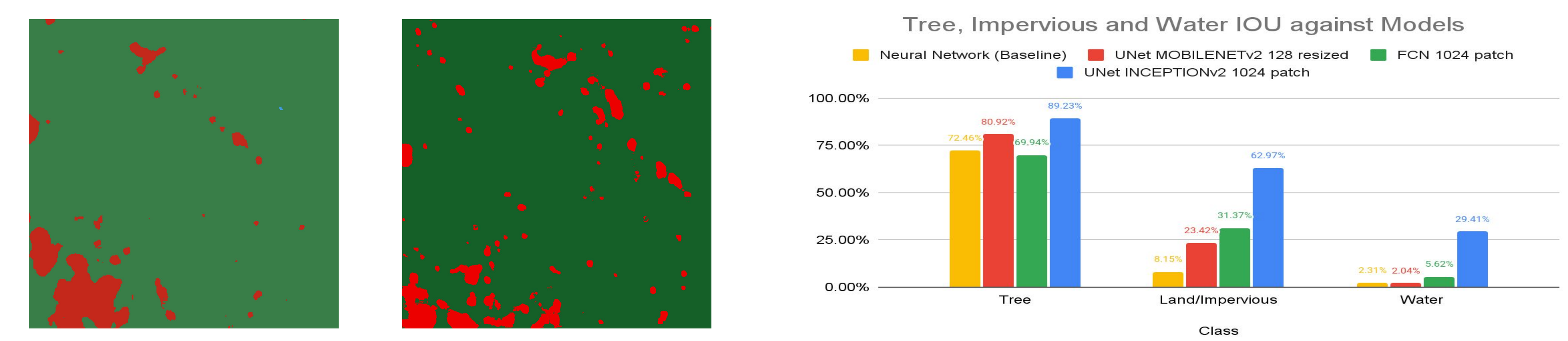


Figure 3. Dynamic world image (L), predicted image (M), IOU for each model across class (R)

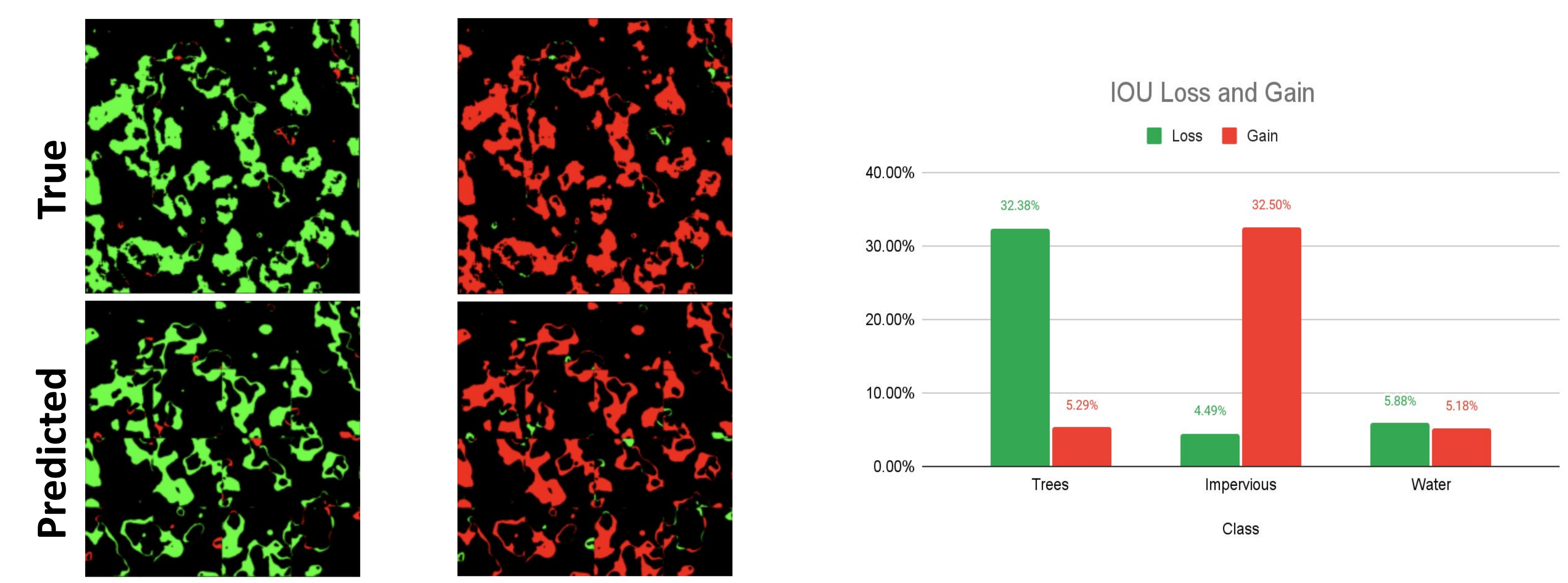


Figure 4. Land cover change between the years Loss (L), Gain(M) & IOU chart for each class (R)

Manual Labeling Results on best performing model:

Comparison	IOU Tree	IOU Land/Impervious	IOU Water
Dynamic World vs Manual	75.97%	14.61%	8.56%
Prediction vs Manual	75.07%	15.03%	11.96%

Conclusion

The developed model has ability to segment and detect land cover change better than random guessing and baseline model. It can be leveraged to get an estimate of important metrics like deforestation rate over time. Future scope includes using high resolution data, training more complex architectures and also segmentation for more than three classes.

Acknowledgments & References

High-resolution land cover change from low-resolution labels: Simple baselines for the 2021 IEEE GRSS Data Fusion Contest https://arxiv.org/pdf/2101.01154.pdf

https://github.com/calebrob6/dfc2021-msd-baseline