Land Cover Classification from Very High-Resolution Satellite Imagery using Deep Learning

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1. Motivation

Land cover (LC) represents the Earth's surface features, which include water, soil, vegetation, and so on with their respective sub-groups. Accurate and timely LC information is important for decision-making processes and resource management at various levels. However, LC mapping is often difficult and time-consuming with the conventional approach. The increased availability of Very High Resolution Satellite Imagery (VHRSI) has given precedent to deep learning (DL) in supervised LC because of their ability to handle big data and produce more accurate results with a considerable balance between accuracy and computational time [1]. Among the various models of deep learning, Convolutional Neural Network (CNN) stands out as the most emblematic, characterized by its deeper architecture and remarkable learning capacity [2].

2. Objectives

1. To identify Land Cover using the U-Net architecture of CNN

2. To assess the performance of U-Net model with and without data augmentation

3. Study Area

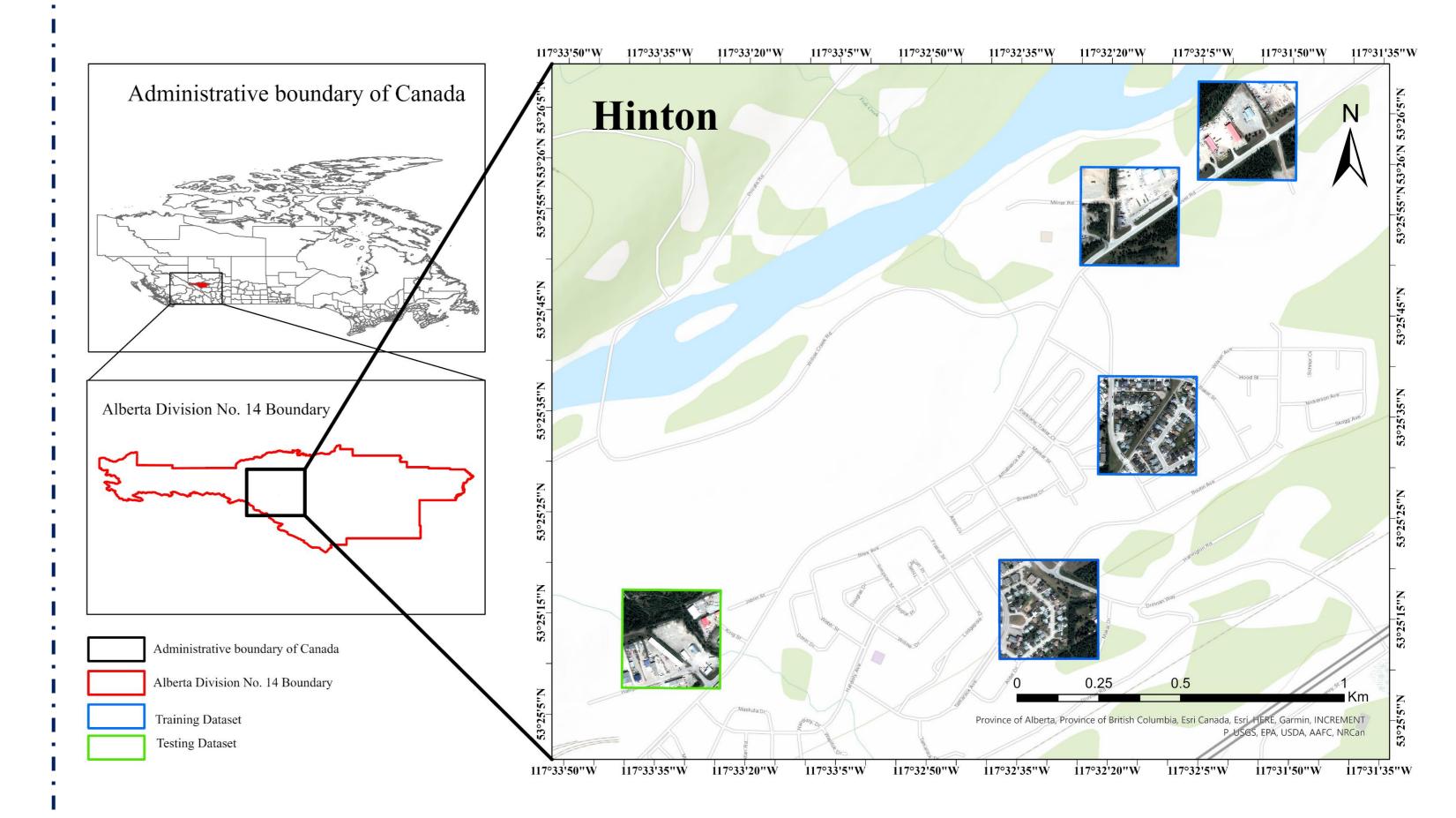
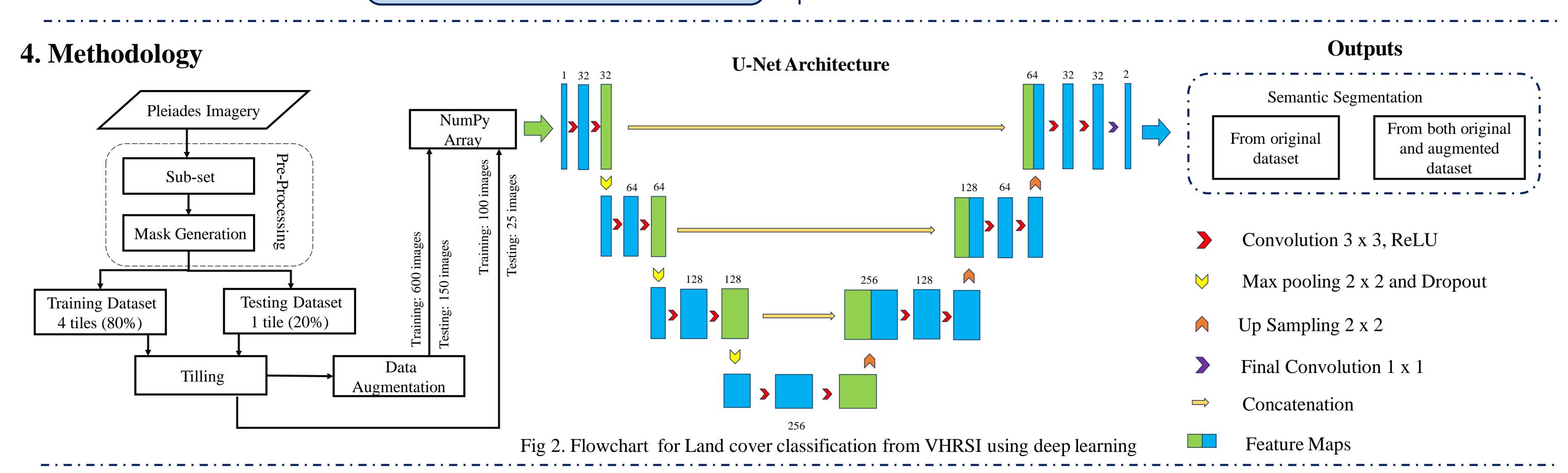


Fig 1. Study area Map Pleiades Imagery (0.5 m) Natural Colour Combination 123 bands



5. Results

Fig 3 shows the results of the land cover classification from the U-Net architecture, a very popular DL model CNN, applied on VHR satellite imagery. The input masks have 6 classes: road, building, needle leaf, broad leaf, barren land, and unlabeled. In this study, image segmentation has been done in two different ways. One is with only the original images. The rest is with both original and augmented images. Five types of augmentation have been applied which are center cropping, horizontal flip, vertical flip, random rotation, and grid distortion. As a result, there is a considerable difference in results between these two. Classification with augmented data is performed better than classification without augmented images. Fig 4 demonstrates that both curves of accuracy and loss produced in both the training and testing stages from data without augmentation have fluctuated highly. Even, the loss is increased (initial loss 0.86 and the final loss 0.98) and accuracy is decreased (initial accuracy is 0.72 and the final accuracy is 0.56) over epochs in the testing stage (Fig 4). On the contrary, using both the original and augmented images, both curves of accuracy and loss are comparatively smooth, produced in both the training and testing stages (Fig 5). The loss is decreased (initial loss is 1.94 and the final loss is 0.78) and the accuracy is increased (initial accuracy is 0.30 and the final accuracy is 0.75) in the testing stage (Fig 5). So, it can be stated that U-Net architecture performs better with larger data.

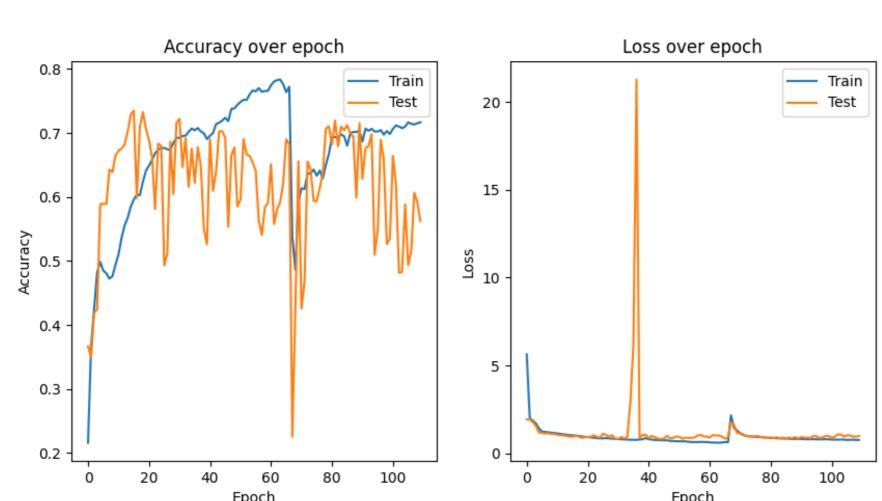


Fig 4. Accuracy and Loss over epoch using only the original dataset

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Fig 5. Accuracy and Loss over epoch using both original and augmented dataset

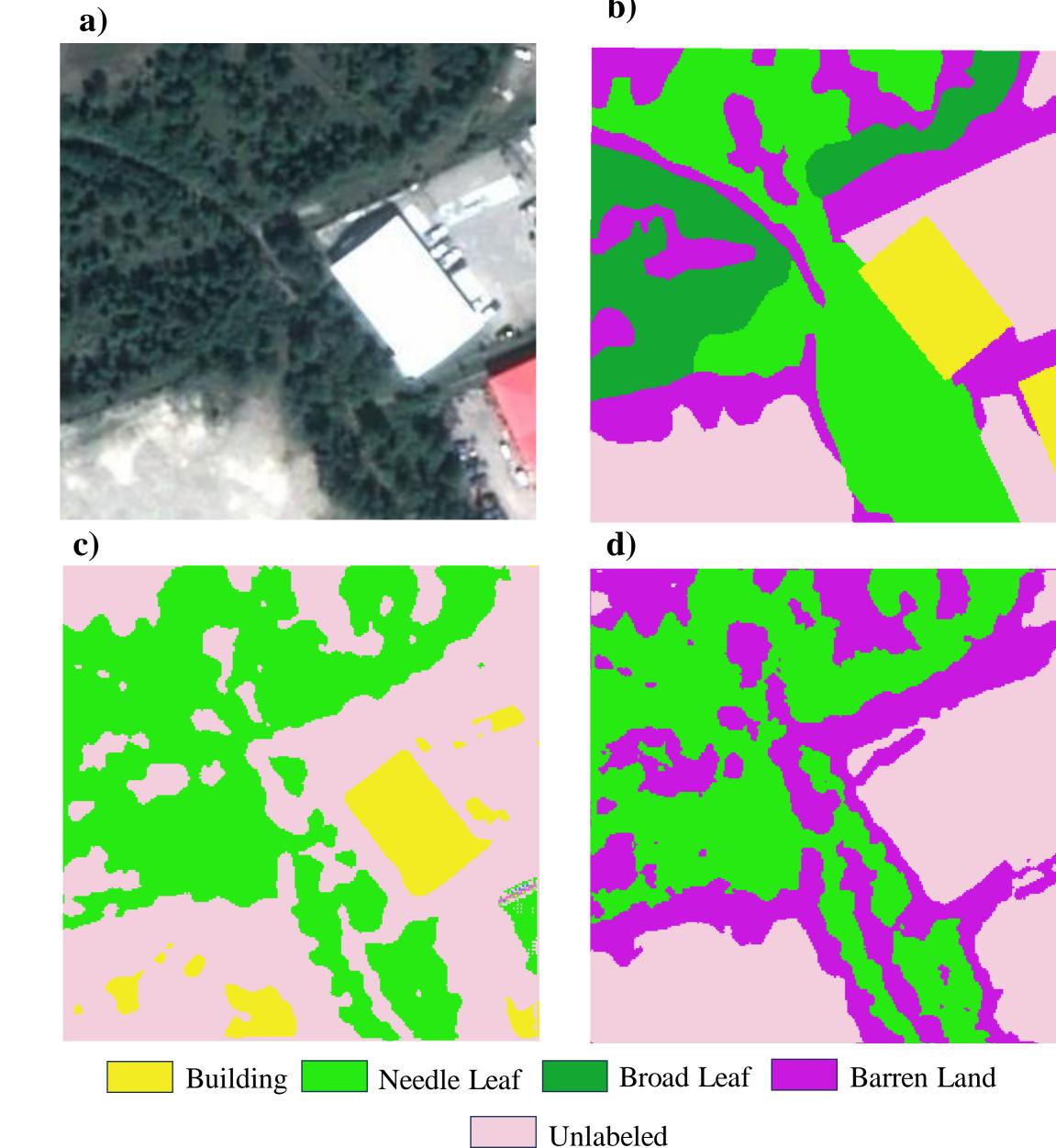


Fig 3. (a) VHRSI (RGB), (b) Generated Mask, (c) Predicted results without augmented data, (d) Predicted results with original and augmented data

6. Conclusion

- Land cover classification is important in sustainable urban and regional planning.
- The present study has performed a U-Net model for land cover classification where it is explored that this model is performed better with larger datasets.
- Future studies should use larger datasets for getting more reliable results.



7. References

- [1] Zhang, L.; Zhang, L.; Kumar, V. "Deep Learning for Remote Sensing Data: A Technical Tutorial on the State of the Art," in IEEE Geoscience and Remote Sensing Magazine, vol. 4, no. 2, pp. 22-40, June 2016, doi: 10.1109/MGRS.2016.2540798.
- [2] Zhao, Z.; Zheng, P.; Xu, S.; Wu, X. "Object Detection with Deep Learning: A Review," in IEEE Transactions on Neural Networks and Learning Systems, vol. 30, no. 11, pp. 3212-3232, Nov. 2019, doi: 10.1109/TNNLS.2018.2876865.

