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Road segmentation in SAR/PolSAR images using Convolutional Neural Networks

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Synthetic aperture radar (SAR) and polarimetric aperture radar (PolSAR) images are remote sensing images captured from an aircraft or artificial satellite to produce topological scans of the earth's surface. The advantage of using these images is that they can be acquired day or night, regardless of the weather. They are used primarily to study deforestation, glacier defrosting, urban growth, and the prevention of natural hazards [3].

Neural networks have successfully solved problems in artificial intelligence (AI) in the last two decades. Among all possible architectures, the Convolution Neural Networks (CNNs) architecture dominates the field of computer vision [2]. CNN is very adaptable and can precisely segment objects in images.

This article's primary approach was to build a synthetic dataset that could be used for training, validation, and testing. Then, the Speckle noise, inherent noise in SAR images, was introduced into the Massachusetts Road Dataset, an aerial optical image database, to create a database that simulates SAR images. We use this database to study how different CNN architectures perform when trained to detect roads.

Our research methodology consists of building a simulated dataset based on the optical Massachusetts Roads Dataset [4] by adding the Speckle noise with a Gamma law represented by a univariate probability density function

$$f_{\mathbf{Z}}(z;\mu,L)=\frac{L^L}{\Gamma(L)\mu^L}z^{L-1}\exp\Big\{-\frac{L}{\mu}z\Big\}\mathbb{1}_{\mathbb{R}_+}(z), \tag{1}$$

where $L>0$, $\mu>0$ is the mean, $\mathbb{1}_A$ is the indicator function of the set A, and $\Gamma(L)$ is the Gamma function.

After this, we trained two CNN architectures: the U-Net architecture[5], which uses skip connections between the encoder and decoder blocks to transfer information, and the DeepLabV3[1] architecture, which uses Atrous Convolution, a technique that changes the kernel size to gather context from multiple scales.

Fig. 1, and Fig. 2 show the results achieved until this research phase on an image chosen arbitrarily in the test dataset.

By visual inspection of Fig. 1 and Fig. 2, and with results shown in Tab. 1, we can note that the U-net shows a slight advantage in road detection over DeepLabV3. We have ongoing work such as measuring road detection accuracy, adding real SAR images to the dataset, or using Generative Adversarial Networks (GANs) to transform optical images into SAR images.

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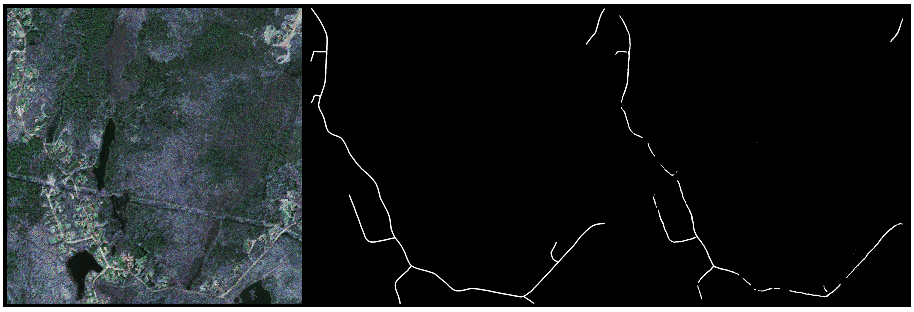

Figure 1: UNet segmentation, 20 epochs training. left: simulated SAR, center: ground truth mask, right: predicted mask. Source: authors.

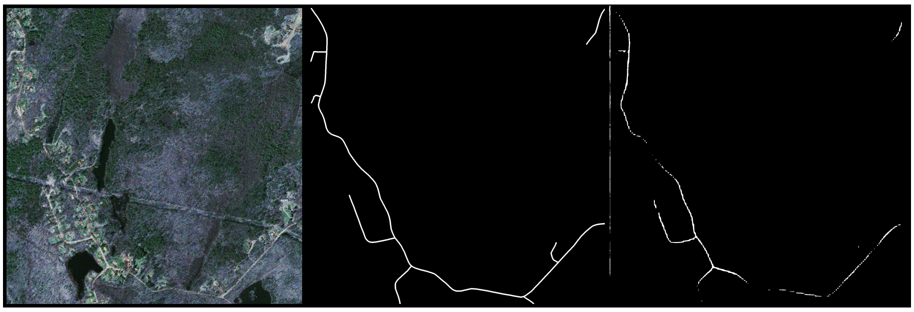

Figure 2: DeepLabV3 segmentation, 20 epochs training. left: simulated SAR, center: ground truth mask, right: predicted mask. Source: authors.

Table 1: Metrics gathered from trained CNNs.

Architecture	Metrics				
	IoU	Accuracy	Precision	Recall	F-Score
U-Net	0.899	0.947	0.919	0.976	0.946
DeepLabV3	0.891	0.943	0.920	0.965	0.942

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