OUT OF DISTRIBUTION DETECTION IN THE SYNTHETIC APARTURE RADAR (SAR) IMAGES

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ABSTRACT

The study presents an out of distribution detection approach in the SAR images which is important for ensuring the robustness and reliability of SAR-based applications, especially in scenarios where the data may deviate significantly from what the model was trained on. We have used a ensemble of pretrained networks and four from scratch trained networks. Temperature scaling is used before computing the SoftMax score for each model.

***Index Terms*—** Out-of-distribution, SAR, Supervised Learning.

1. INTRODUCTION

In the context of supervised learning, out-of-distribution (OOD) detection refers to the task of identifying samples that differ significantly from the training data distribution. These samples are often not well-represented by the training data and may cause the model to make unreliable predictions. There are various methods used to counter the OOD, one of which includes ensemble methods combining predictions from multiple models trained on different subsets of the data or using different algorithms. Disagreement among ensemble members on the prediction for a particular sample may indicate that it is OOD.

2. STUDY AREA AND METHODOLOGY

The training dataset consists of 28 single band SAR images with their respective labeled ground truth masks. For the test dataset, the predictions are run over the set of 10 single band Sar images.

2.1. Training and Test Dataset

For training we have randomly selected 28 of the images and remaining 20% for the validation set. Each of the training images is 1024*1024*1 dimensions with each corresponding label of 1024*1024*1. Later the training set is divided into training and validation with the ratio of 80:20. In training images labels Valid classes are denoted by red, green, and yellow colors whereas black denotes unknown.

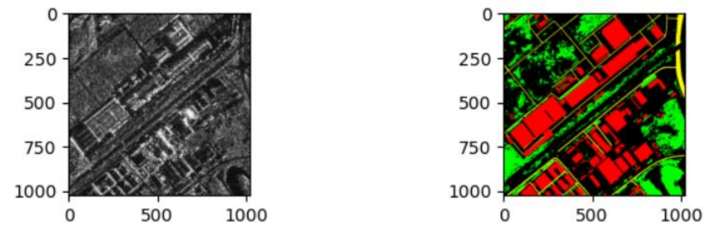

Figure 1: Train Set

The test dataset consists of SAR images of the same 1024*1024*1 as the testing dataset.

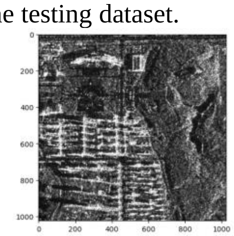

Figure 2: Test Set

2.2. Ground Truth Labels

In this case we are training the model using 3 actual classes. For Actual class label we are making general one hot vector but for unknown in the training sample using one hot with each class of taken class probability of [0.33,0.33,0.33].

2.3. Model

In this study a total of five models are used namely starting with one pretrained model Seresnet34, and four normal U-Net variants with different initializer, regularizer and activation functions. We are saving the best model out of five models.

2.4. Loss Functions and Metrics

Each of the models is trained for 200 Epochs with optimizer being Adam optimizer learning rate 0.001. The combination of dice and focal loss with the class weightage [0.22,0.16,0.4] for red, green, yellow class labels respectively.

For the metrics we have calculated Overall Accuracy (OA%) and Intersection over Union (IoU).

2.5. Temperature Scaling

We did temperature scaling of all five models for calibration which is to ensure best temperature value for each model one by one, which minimise the negative loss likelihood based on the validation data. For this we have used Adam optimizer with Learning rate 0.01 and 500 iterations. The value of the T is as follows for each of the model.

Model	Temperature Scaling (T)
Seresnet34	3.1619246
U-Net-1	0.3140936
U-Net-2	3.071475
U-Net-3	3.101913
U-Net-4	0.24277015

2.6. Ensemble of Models

Ensemble of each of the five models to get the SoftMax score on temperature scaled logits. For each of the model we find the difference between the maximum SoftMax score and the second max SoftMax score if it is greater then threshold 0.05 then the label will be the class with maximum SoftMax score, otherwise it will be OOD. after getting the labels using each of the five models, we assign the final label of the pixel as most of the classes for that pixel.

2.7. Generating Test data Labels

The prediction labels are generated for each of the test images which are three channels where each pixel is either red [255,0,0] or green [0, 255, 0] or yellow [255, 255, 0] or novel unseen during training process: blue [0, 0, 255] where blue is OOD. Finally, we are saving the generated labels in the PNG format.

3. RESULTS & DISCUSSIONS

The following results are obtained for training the models on the validation dataset.

Performance	Seresnet34	U-Net 1	U-Net 2	U-Net 3	U-Net 4
OA (%)	46.60	23.57	15.01	62.08	69.89
IoU	0.1011	0.0483	0.0484	0.0486	0.0484

The Training and Validation curve using SeResnet34 and U-Net 3 are as follows:

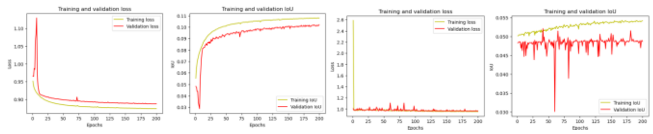

Figure 3: Training and Validation SeResnet34 and U-Net 3

3.1. Test data labels

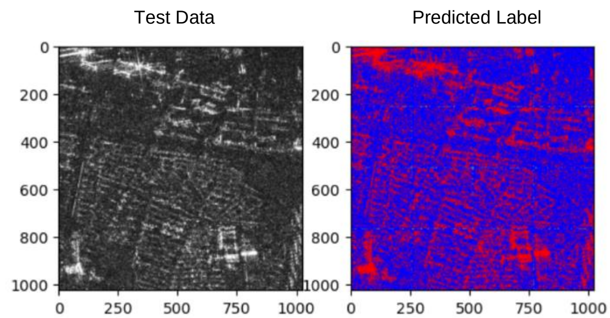

Figure 3: Test data and it's Predicted Label

The predicted labels generated using the approach show a significant amount of out-of-distribution (OOD). This can be due to the fact of the noise present in the SAR images which makes its saliency low thus learning the features from a small amount of the training data challenging. It is also worth noting that the second most prominent class is Red followed by Yellow and Green in the testing dataset.

4. REFERENCES

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