Mid-term Report: River Network Detection Project

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1 Summary of Accomplishments

1.1 Code Completion for Training

- Identified and rectified a few errors which were present in the codes after summer.
- Few errors included the number of corrupted pixels exceeding the threshold, caused due to incorrect procedure while corrupting, an example of which is shown in Figure 1

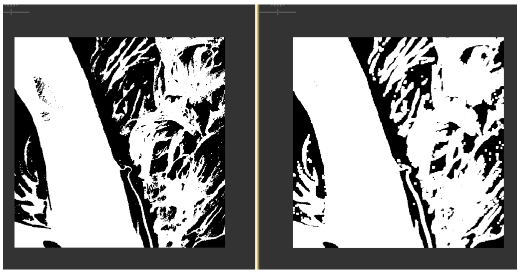

Figure 1: Wrong corruption model

1.2 Retraining of Vanilla UNet

- Retrained the Vanilla UNet model to allow for a 70:10:20 train:val:test split, with 20 epochs.
- The results show a very good performance for the UNet model without any corruption. They are shown in Table 1

1.3 Adversarial Training

- Started Adversarial Training for the UNet Model with the same train test split as provided for the Vanilla UNet.
- 1/3rd of the training and validation data is corrupted using Erosion, 1/3rd by Dilation, and 1/3rd is kept untouched.
- Randomness is brought about in the corruption by introducing randomness in the size of the kernel window used for erosion and dilation, with higher kernel sizes preferred for images with a higher white pixel ration for erosion, and vice versa.
- The results for adversarial training are shown in Table 1

1.4 Visualisations

- Began Qualitative and Quantitative analysis of the results uing Visualisations.
- Wrote codes to visualise the training of each of the models across epochs to observe the variation in accuracies, and observe the effect of the corruption levels.

- Wrote codes to visualise the predicted masks and expected masks for the test data to perform qualitative analysis of results. Some results are given below.

1.5 Work on the Paper

- Started writing the paper, and written all of the work done so far in the paper.
- The paper primarily consists of our work with making the dataset using NDWI Index [15], preprocessing techniques [3, 13, 8, 7], training approaches [12], models used, and our results with adversarial training. All qualitative and quantitative results so far have been included in the paper.
- We also dive deep into related works [9, 10, 1, 16, 14] and provide some background theory on a number of techniques that we use in the paper.

1.6 Readings

We are currently looking into other models of corruption, for which we are currently reading other papers. Some links to papers we are currently reading include -

- Unsupervised Domain Adaptation for Remote Sensing Image Semantic Segmentation Using Region and Category Adaptive Domain Discriminator [2].
- Domain Adaptation using NDWI index for Water-land Semantic Segmentation [4].
- VQUNet: Vector Quantization U-Net for Defending Adversarial Attacks by Regularizing Unwanted Noise [5].
- Bit-Flip Attack: Crushing Neural Network With Progressive Bit Search [11].
- Metapoison: Practical general-purpose clean-label data poisoning [6].

2 Next Steps

1. We need to now begin experimentation with a few more corruption models and techniques, whose results we can include in the paper.
2. We are currently looking into more types of corruption, including more traditional types such as rotation etc, and other corruption techniques outside of erosion and dilation. We are currently looking into these possible methods.

3 Results and Inferences

3.1 Quantitative Results

Table 1 shows the results for the various metrics, for the various levels of corruption tested so far. The results clearly suggest that the model is able to adjust well to even moderate levels of corruption, being able to tolerate upto 12% corruption without loss in accuracy, while accuracy falls considerably for a higher corruption.

Table 1: Performance Metrics of U-Net Model

Metric	**Clean UNet**	**2% corruption**	**12 % corruption**	**20 % corruption**
Average Dice Coefficient	0.7696	0.7748	0.7693	0.0541
Average IoU	0.8230	0.8252	0.8224	0.4150
Average Pixel Accuracy	0.9554	0.9546	0.9546	0.8045
Average Precision	0.8959	0.8959	0.8989	0.7425
Average Recall	0.8688	0.8734	0.8641	0.5134
Average F1 Score	0.8652	0.8677	0.8646	0.4642
Average Specificity	0.9708	0.968	0.9748	0.9988
Model's Overall Accuracy	0.9554	0.9546	0.9546	0.8045

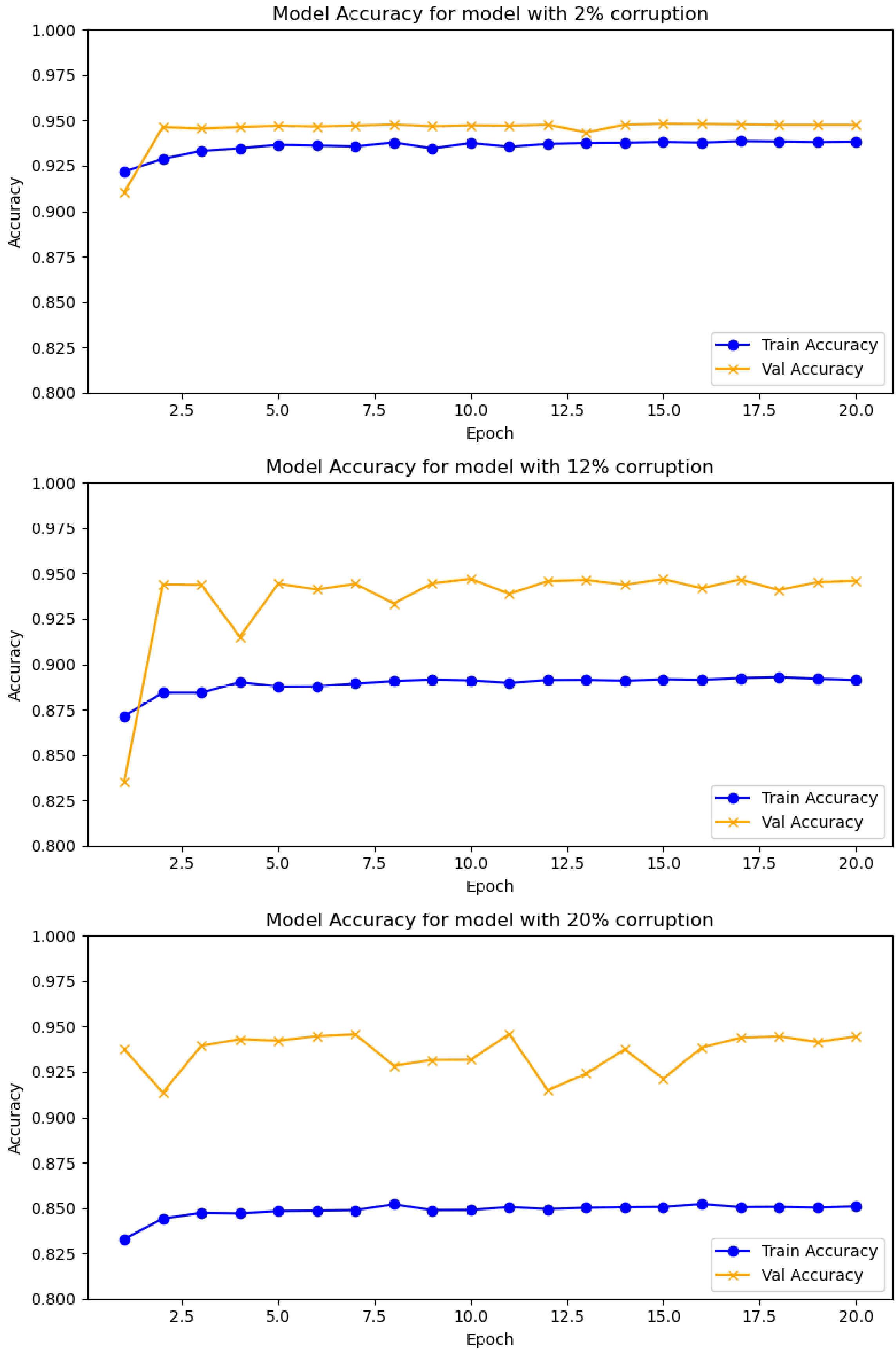

Figure 2: Epoch Data for all the three models

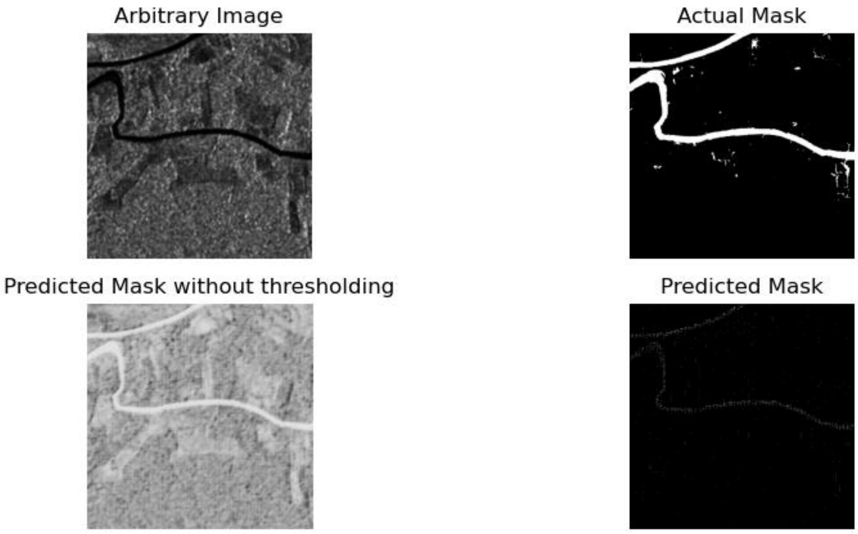

Figure 3: Image, actual mask, predicted without thresholding, and predicted mask for 20% corruption model

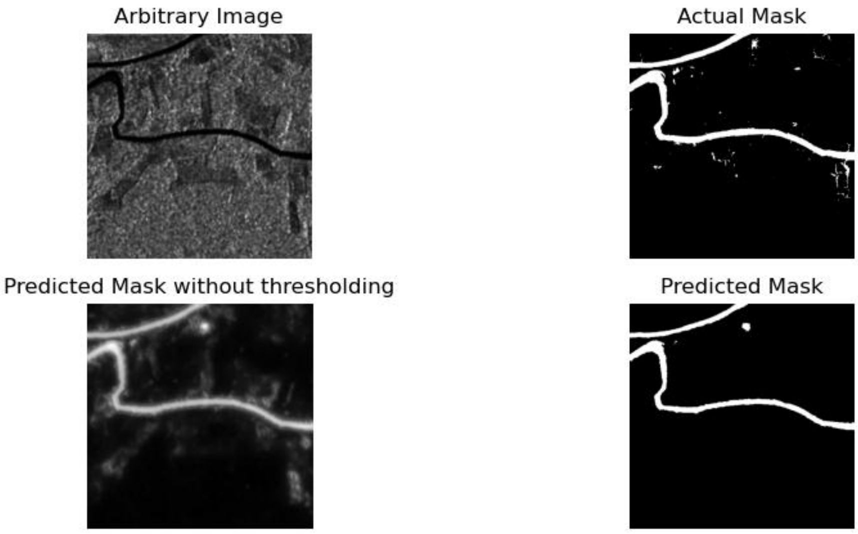

Figure 4: Image, actual mask, predicted without thresholding, and predicted mask for 12% corruption model

3.2 Training Trends and Inferences

The validation accuracy trends for all the three models shown in Figure 2 indicate that the model does not overfit, as is also indicated by the decreasing training accuracy as the corruption level increases. However, the model with 22% corruption is not able to perform well on the test data, unlike the models with 12 % corruption, and 2 % corruption.
This suggests that the model is able to tolerate and not overfit to only certain levels of corruption, while performance degradation occurs at higher levels.

3.3 Qualitative Examples

The example images shown in Figures 3, 4 and 5 indicate that with the increase in corruption levels, it becomes increasingly difficult for the model to distinguish land from water, although a little distinguishing is possible before the threshold is applied. To get a proper mask, we will need adaptive thresholding, otherwise the model with higher corruption will not work well.

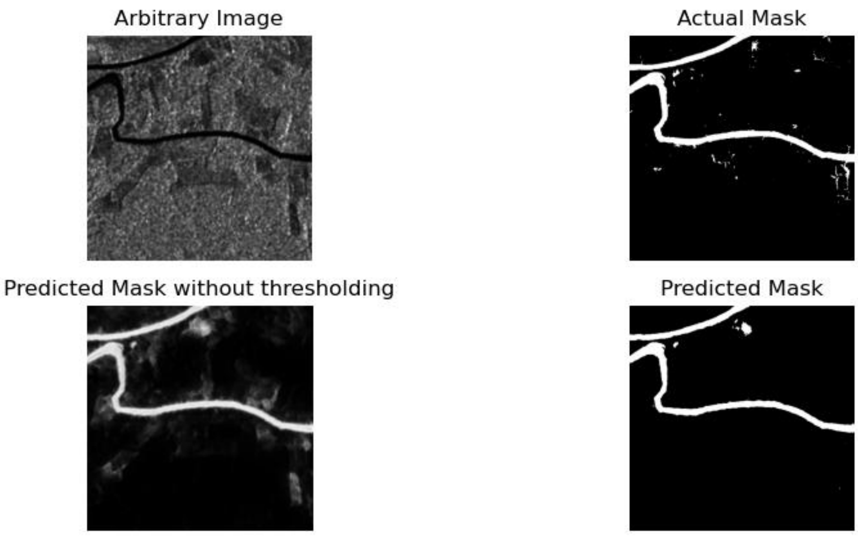

Figure 5: Image, actual mask, predicted without thresholding, and predicted mask for 2% corruption model

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