Predicting Radar Image Using Conditional GAN From Satellite Images

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Abstract—Currently there is no radar information over the ocean, just satellite images. However satellite cannot tell us the rainfall data, while radar can. If successfully carried out, we can get rainfall data just using satellites and even prevent upcoming weather rain storms. The goal of this project was to use a conditional GAN with time sequence, to transform satellite image into radar image so that we can obtain rainfall over the ocean and forecast major weather conditions. This paper will discuss the usage of a machine learning model, vid2vid, to solve this problem.

While pix2pix[2] has been used for this problem, vid2vid[1] is a another conditional GAN that takes into consideration of the time sequence, so it should produce a radar images in a sequence, where the next images are similar in optical flow as the previous images.

Introduction

Radar stands for Radio Detection And Ranging. It can detect motion in a given location range, and provide values like speed of rainfall using radio waves that bounces off anything that blocks its way. This information is especially valuable especially to detect thunderstorms which can cause severe damage. It can damage not only infrastructures but take human lives as well. There has been many heavy storms in the past that damaged people's homes and taken lives, therefore it is crucial to know rainfall not only over land but over ocean as well. An example would be Puerto Rico between 2003 to 2005. Within that time frame, PR had 5 severe rain storms that severely impacted human lives and the economy as well [1].

The satellite data given to us are from the GOES13 satellite, an american satellite. GOES13 has 6 total bands, that detects things like clouds, low clouds, fog, fire, surface temperature etc. We are currently have information from all bands except 5. The increments of which these images were taken varies. While GOES13 takes pictures every 30 minutes, the radar images capture every hour. Even though there are satellite images over the ocean, they do not give precipitation data. This issue can be solved with a deep machine learning model, like pix2pix [2] or vid2vid [3].

Background

There has been many research done in over the ocean, one of them includes "*Machine Learning for the Detection of Oil Spills in Satellite Radar Images*" [5]. It tackles oil spill detection and addresses problems like problem formulation, and data preparation. The images used for training were RADARSAT and ESRS-1 images. And they produced a classifier in the shape of a decision tree to solve this problem. GANs [4] are a popular way to solve problems like generating under water images [6] and get better quality underwater images. This is done by converting air images into under water image in batches.

The pix2pix model is a recent machine learning model that utilizes a conditional generative adversarial network [3]. There is a generator that generates the output image, while there is also a discriminator that judges the output image, and results of the model can be seen in figure 1. Since pix2pix is just a image to image model, there are times where there are drastic differences between two images. It is unreasonable to have big cluster of rain come out of nowhere in the next image, so vid2vid will help with that issue, since our data is a time sequence, vid2vid would help the output image to have a smooth optical flow.

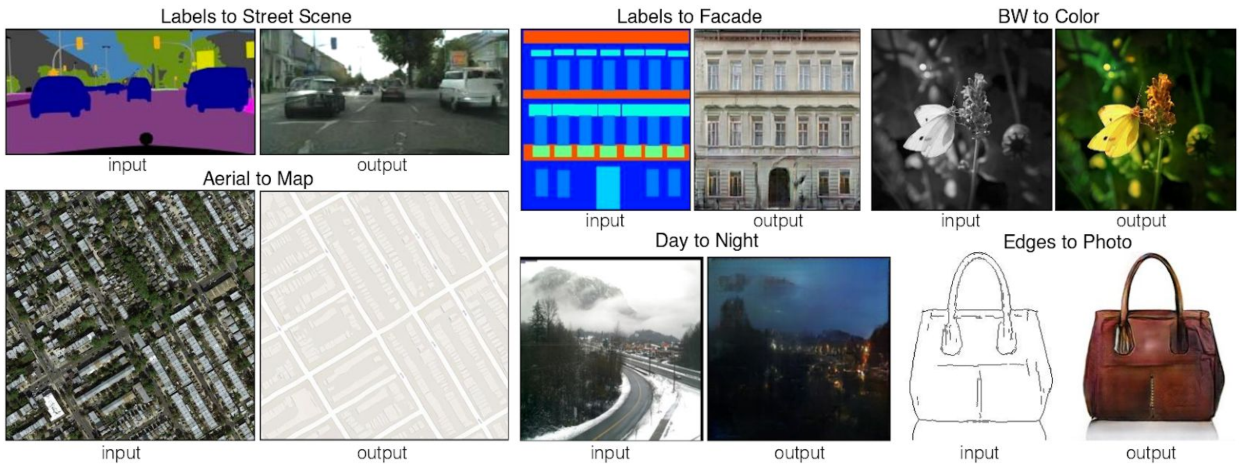

Figure 1: This figure shows the many problems in image processing, graphics, and vision involve translating an input image into a corresponding output image. The above are results of pix2pix transformation.

Vid2vid is a video synthesis model that aims to produce realistic videos without having to explicitly specifying scene geometry, materials, lighting, and dynamics. With carefully-designed generators and discriminators, and a new spatio-temporal learning objective, the Vid2vid model can learn to synthesize high-resolution, photorealistic, temporally coherent videos [3]. This model is also built on GANs [4], with the discriminator and generator playing a zero sum game. For $S_1^T = \{S_1, S_2, \dots, S_T\}$ as a sequence of video frames, and $X_1^T = \{X_1, X_2, \dots, X_T\}$ as the corresponding real video frames, Vid2vid learns a mapping function to convert $\{S_1, S_2, \dots, S_T\}$ to $\dot{x}_1^T = \{\dot{x}_1, \dot{x}_2, \dots, \dot{x}_T\}$ where the conditional distribution of $\dot{x}_1^T$ is identical to X_1^T given S_1^T. The generator for this model is trained by solving the minimax optimization problem below:

$$\max_D \min_G E_{(\mathbf{x}_1^T,\mathbf{s}_1^T)}[\log D(\mathbf{x}_1^T,\mathbf{s}_1^T)] + E_{\mathbf{s}_1^T}[\log(1 - D(G(\mathbf{s}_1^T),\mathbf{s}_1^T))],$$

However what makes Vid2vid promising to our problem statement is that it has a conditional video discriminator, which ensure that consecutive output frames resemble the previous ones, thus ensuring a smooth optical flow.

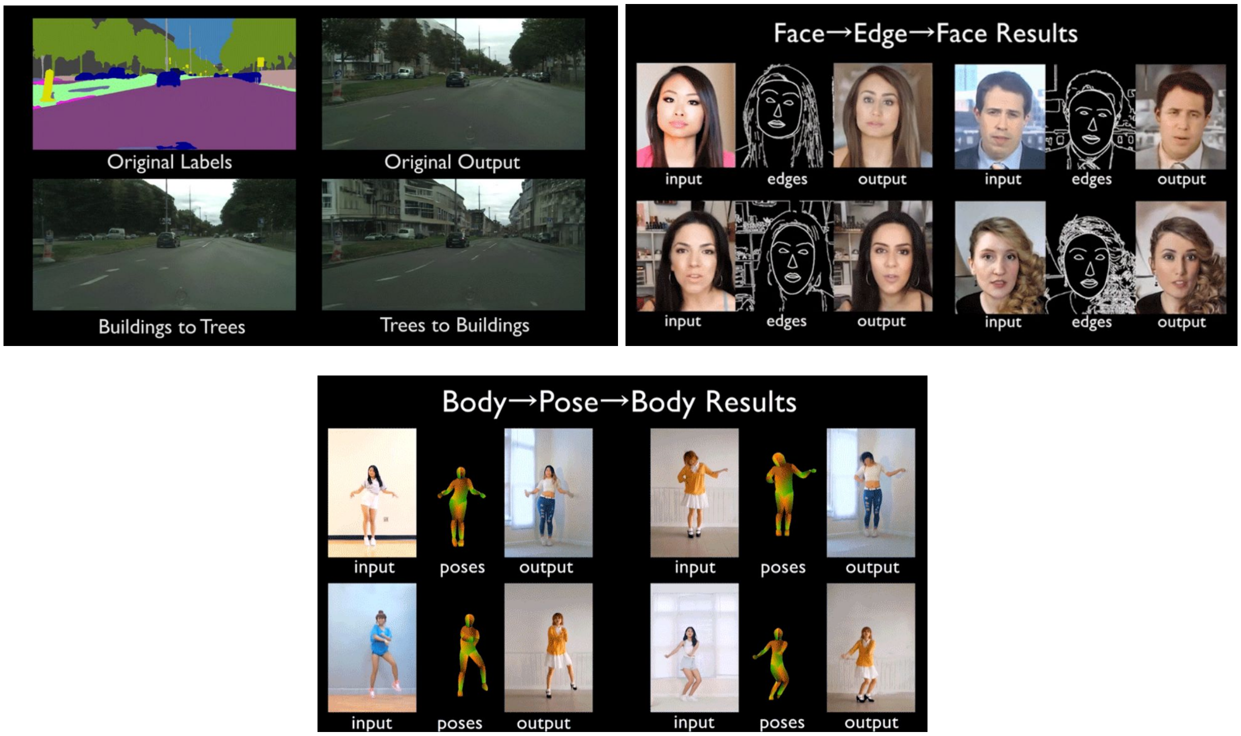

Figure 2: The picture above shows the different outputs of vid2vid, with different type of training data like, label maps, edge maps etc.

Method

There were 3 teams, data management team, algorithms team, and evaluation team, and I was apart of the algorithms team. This means I worked with Vid2vid for data that I received from the evaluation team, and then the results were then evaluated by the evaluation team. Different GANs were explored, pix2pix and vid2vid, and they both gave interesting results. We also performed linear regression and random forest as a base model.

Data

While trying to match satellite images with radar images, we encountered many problems. The frequency of the satellite and radar images were off by 15 minutes, and both had time frames where there were missing images. We also went through all the images that were sparse and mostly black and decided they were unusable. This decreased the amount of usable data significantly. Another problem that became an issue for vid2vid was that there were not enough sequences of 30 images, because most frequency length of images were between 5 or 10, which did not yield great results.

Linear Regression/Random forest

A linear regression model and a random forest model was used as a baseline model to compare other deep machine learning models to. Since linear regression is pixel to pixel mapping, if we can solve the problem with a simpler algorithm, then there is no need to use something like a GAN.

Pix2pix

One team member utilized pix2pix to train on our satellite and radar data. There were several models trained with model data and without model data. The model data is from the North American Mesoscale data set

As specified in the research paper [3], vid2vid is ran with 8 GPUS, 4 for generators and 4 for generators, so the first challenge would be to get vid2vid to work on 1 or 2 GPUs. Since vid2vid is a relatively new paper published, there is not that much of a established community that utilized it. A lot time was spent on their github issue page asking clarifying questions.

Since vid2vid has a extra layer or video discriminator, they utilize FlowNet which is another model that I have to set up. There were many issues encountered on the GPUs given, there were not enough storage space to put both vid2vid dataset and pix2pix datasets. Another problem encountered was that I kept encountering CUDA errors, but even found others who got the same error on the issues page but no one explained how to fix the issue. The next step was to work on google Colaboratory free GPU, and set up the CUDA environment there. However I continuously ran into out of memory errors and realized and pxi2pix is not compatible with Tesla V80 GPUs because FlowNet architecture setup does not include the V80 GPUs.

on the NOAA website. The model is ran several times with different datasets. The first data set was with satellite band 2, 6, model data's temperature, visibility, specific humidity and relative humidity. To improve the amount of data in training, the images were flipped 3 times.

Vid2vid

Finally I moved onto purchasing a GPU on Google Cloud Computing, and trained with 30 sequence length images, that are 256 x 128 resolution image. The image had to be scaled down since I only worked with a single GPU. The data used to train vid2vid is satellite band 2 and the corresponding output radar image. Since the video sequences are decided to be 30 because shorter video lengths outputted black images as results, this cuts down significantly the training data to 180 images, which is nowhere near enough to train a deep learning model to output good results.

Results

The results of the base model like linear regression shows that the results were not as a promising as conditional GAN like pix2pix. The figure below shows the results with different thresholds, and the confusion matrix of the results show that 17 percent of the time when it is raining, the algorithm will predict rain.

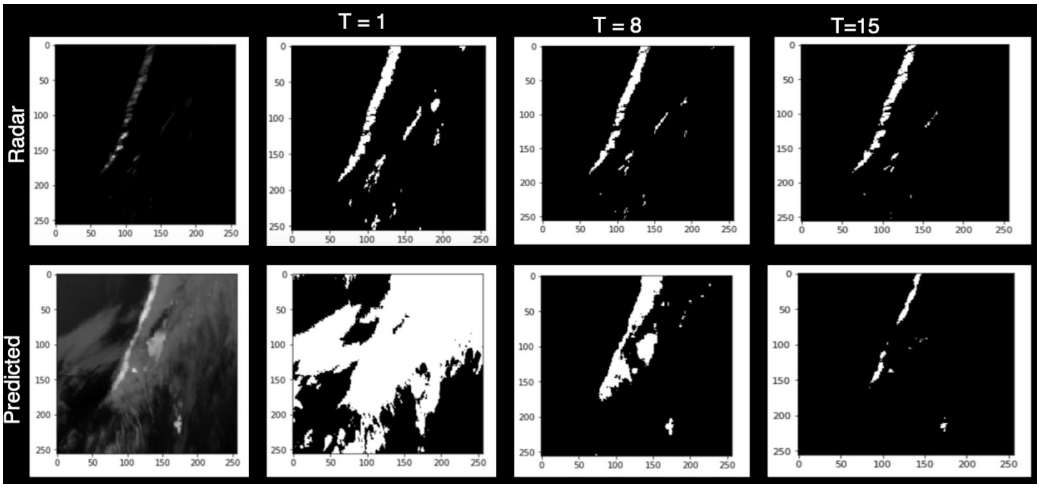

Figure 3: This image shows the results of linear regression with different thresholds.

Pix2pix

The results of pix2pix were the most promising, as it is trained with model data along with satellite data. As you can see in the figures below, it does a pretty good job at predicting where the rain is based off the input data. According to the confusion matrix, 53 percent of the time when there is rain, it accurately predicts rain, which is a lot better than the base models.

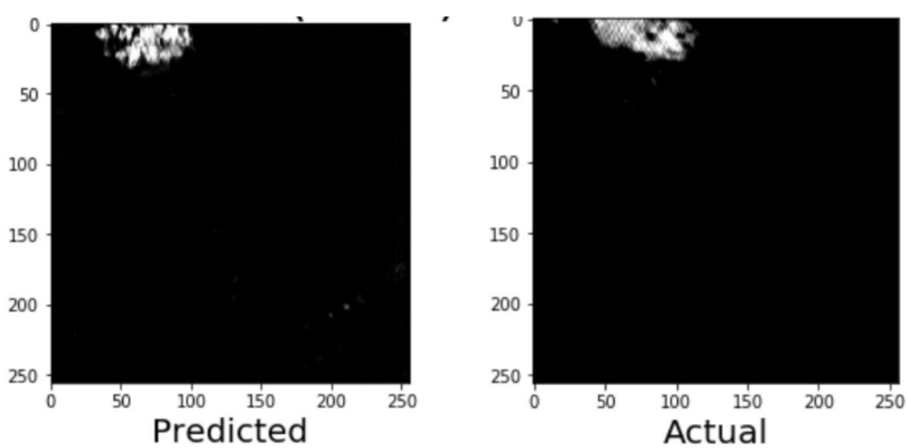

Figure 4: This image shows the result of the pix2pix model.

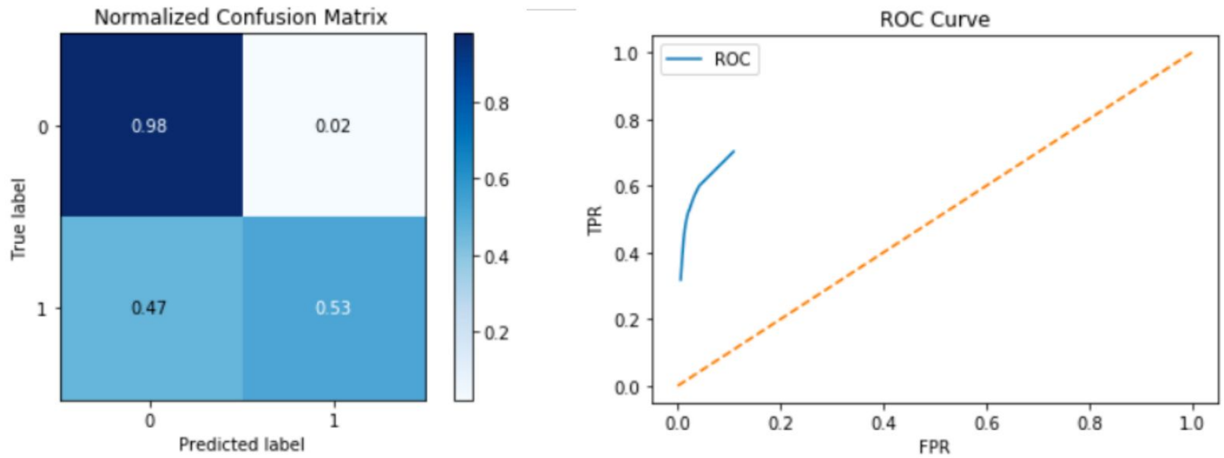

Figure 5: This is the confusion matrix and ROC curve of the pix2pix model.

Vid2vid

Vid2vid aims to solve the problem of having choppy output images, since our data is a continuous sequence. While pix2pix is just image to image transformation, vid2vid address that issue. Since we only had 180 images to train with, the results were not very good as you can see below. The confusion matrix shows that only 2 percent of the time when it's raining, it will predict rain.

However, the output results are more smooth optical flow and it looks like a time sequence video. While the results were bad as expected, it does show that vid2vid does provide a smooth optical flow to the input data.

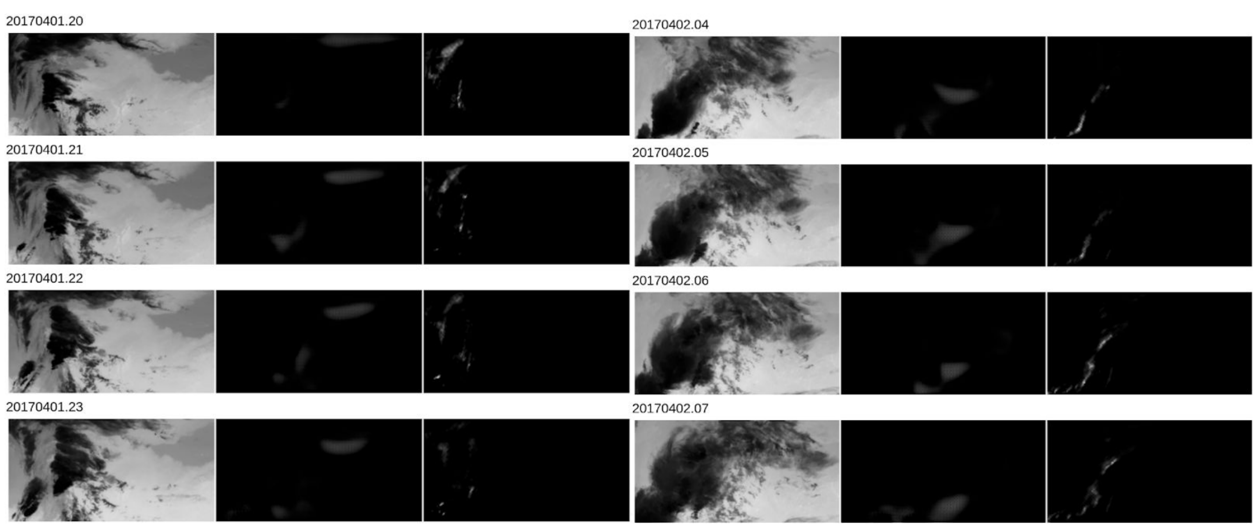

Figure 6: This is the results of the vid2vid model, with satellite, output, and expected radar image.

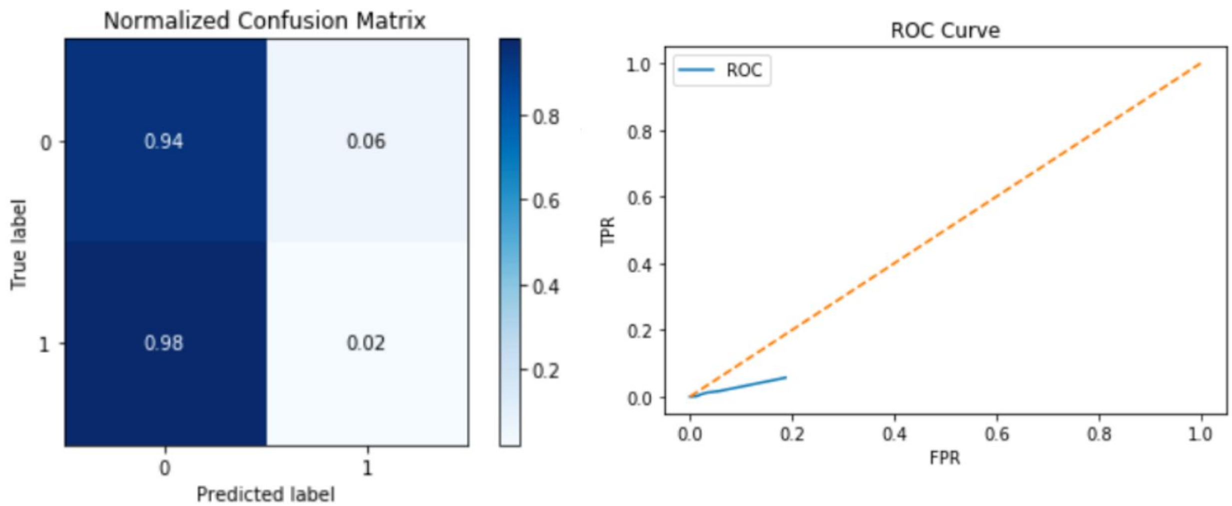

Figure 7: this is the confusion matrix, ROC curve of the vid2vid results.

Conclusion

Since derving radar data over the ocean is not yet a popular topic, utilizing the newest machine learning algorithms to solve it was really interesting. Out of all the algorithms, pix2pix performed the best as it was given the most data to train with. Although vid2vid did not perform well, it also did not have any where near the amount of images pix2pix trained with.

Vid2vid is an expensive algorithm to run, as mentioned in their paper, they used 8 GPUs to train on their sample data, and trained for about 8 days [3]. Although I only ran it on 1 GPU, the results are smooth, so if there were more data available and more investment in GPUs, vid2vid would be a great algorithm to invest in.

References

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